Recovery Dynamics: An Explanation from Bank Screening and Entrepreneur Entry*

Yunzhi Hu†

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Abstract

Economic recoveries can be slow, fast, or involve double dips. This paper provides an explanation based on the dynamic interactions between bank lending standards and firm entry selection. In the model, bank lending standards refer to both how banks screen borrowers with unknown quality and whether well-qualified borrowers are credit rationed, and firm entry selection refers to the mechanism through which financing conditions select firms of different quality to enter the lending market. Recoveries are slower when high-quality borrowers postpone their investments, which occurs if the borrower pool has lower quality on average. Double dips can occur when banks endogenously produce information, which increases waiting benefits discontinuously. The model is consistent with both aggregate- and industry-level data.

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†Email: yunzhihu@chicagobooth.edu

1 Introduction

There is no agreement on why the recovery from the Great Recession has been slow.[1] Some people blame the financial sector for limited credit supply, whereas others emphasize weak credit demand.[2] This paper presents a theory that reconciles both views. In doing so, it explains why recoveries can be slow, fast, or involve double dips,[3] as well as how the financial sector affects recoveries.

The explanation is based on two ingredients: (1) bank lending standards; and (2) firm entry selection. Bank lending standards include how banks *screen* borrowers with unknown quality and whether well-qualified borrowers are credit *rationed*. Lending standards are low when banks provide credit immediately to all borrowers without rationing or screening (unscreened credit). In contrast, lending standards are high when banks only offer credit after carefully screening borrowers (screened credit). Since screening takes time to accomplish, some borrowers are rationed. Moreover, the standards are highest when the lending market freezes entirely, such that neither screened nor unscreened credit exists. The second ingredient of the explanation, firm entry selection, refers to the mechanism through which financing conditions naturally select firms of different quality to enter the lending market. For example, credit booms are generally accompanied with a deterioration in credit quality.[4] Existing studies have shown that both bank lending standards and the quality of new firms are counter-cyclical (Lown and Morgan, 2006; Lee and Mukoyama, 2015; Moreira, 2015; Ates and Saffie, 2014).

These two ingredients could explain the recovery in business investments, which may be strategically delayed when current financing conditions are unsatisfactory. In particular, I differentiate

[1] An incomplete list of proposed explanations includes policy uncertainty (Baker et al., 2012), regulatory policy (Taylor, 2014), structural changes in the labor market (Jaimovich and Siu, 2012), belief (Kozlowski et al., 2015), and of course, credit market disruptions (implied by Chodorow-Reich (2014)).

[2] For example, during a public speech at the Economic Club of New York on Nov 20, 2012, Ben Bernanke says, "the caution in lending by banks reflects, among other factors, their continued desire to guard against the risks of further economic weakness" (https://www.federalreserve.gov/newsevents/speech/bernanke20121120a.htm). Meanwhile, household indebtedness (Mian and Sufi, 2011) and excessive cash holdings (Sánchez et al., 2013) by corporate firms seem to suggest that credit demand is low.

[3] A double-dip recovery occurs if the economy falls into recession, recovers for a short period, then falls back into recession before finally recovering.

[4] See Asea and Blomberg (1998); Lown and Morgan (2006) for bank lending, Greenwood and Hanson (2013) for the public bond market, and Nanda and Rhodes-Kropf (2013), Gompers and Lerner (2000) for the venture capital-backed startups.

between *entry* and *borrowing*: while the former is defined as entrepreneurs' preliminary actions such as writing business plans and running pilot experiments, the latter refers to firms actually obtaining financing and producing output. Upon entry, entrepreneurs may strategically *wait* rather than borrow immediately. Such waiting and the resulting delay in investment may be optimal since both the borrower pool changes endogenously and banks react endogenously.

More specifically, my model introduces a standard adverse selection problem in the lending market. Firms are of either high or low quality. They apply for loans from banks who are ex-ante uninformed of borrowers' types. Banks can either offer unscreened credit (*pooling* offers) or *screen* borrowers over time and provide credit after becoming informed. I enrich the standard model along two important dimensions. (1) It allows for dynamic information production; banks are endowed with screening technology that enables them to learn the true quality of borrowers over time. Consequently, banks and borrowing firms can decide when to issue/accept a loan. (2) It endogenizes the *average* quality of borrowers in the economy–a key variable that determines equilibria–through the entry decisions of potential entrepreneurs.

Taken together, these two dimensions generate a new mechanism through which high-quality borrowers decide when to invest: their decisions take into account the dynamic effects from new borrowers' entry and bank screening. I first show that the effect from new borrowers' entry alone can generate incentive to wait after recessions, defined as transitions from high to low levels of productivity. Intuitively, cost of waiting (i.e., delaying investment) is low when productivity is also low. Meanwhile, the benefit of waiting can be high, since the *marginal* quality–the quality of entrepreneurs who are about to enter and start new businesses–exceeds the average borrower quality, and thus the borrower pool improves over time. I show that high-quality borrowers wait if the average borrower quality is below a threshold. If this is the case at the onset of a recession, investments are postponed, and a slow recovery follows. Otherwise, the recovery is fast.

Therefore, whether slow recovery occurs depends on the average borrower quality at the onset of recession, which in turn is determined by the size and length of the preceding economic boom. In booms–defined as times with high productivity–the cost of delaying investment is high, and high-quality borrowers have less incentive to wait. Instead, they accept unscreened offers. Catering to their demand, banks endogenously issue these offers, which means low-quality firms can also receive financing. As a consequence, many low-quality potential entrepreneurs enter the lending market, and thus the quality of the borrower pool deteriorates over time. If the boom is large and has persisted for a long time, the average borrower quality becomes very low.

Two additional results are obtained when endogenous bank screening is introduced. First, the market could completely freeze, in which case no credit is available to any borrower. Second, a double-dip recovery may occur. Let me explain the mechanism behind these results. When the average borrower quality is low, banks endogenously choose low or no screening effort, since the borrower will most likely be of low quality and have no profitable investment potential. Under low screening, waiting benefit arises from the improvement in the borrower pool, and thus waiting is optimal if the average quality is below a threshold. Knowing they will only attract low-quality borrowers by making unscreened offers, banks decide to not make them. Such waiting generates a drop in investment–the first dip, during which the lending market experiences an *initial credit freeze*. When the average quality increases above this threshold, high-quality borrowers prefer to take pooling offers, and thus *unscreened credit with high interest rates* becomes available to any borrower. Intuitively, terms on unscreened credit have improved moderately, and waiting for screened credit is too costly because banks will not increase screening effort in the near future. This leads to a temporary rise in investment. However, banks will switch to high screening effort when the average quality improves sufficiently, because the expected profits from screening exceed the cost. Expecting this switch soon, high-quality borrowers stop accepting pooling offers a bit earlier. This generates the another drop in investment–the second dip–during which the lending market experiences a *second credit freeze*. Meanwhile, the borrower pool continues to improve, and eventually, *screened credit* begins, leading to a tepid recovery. Finally, *unscreened low-interest credit* is available after the average quality further increases, which accelerates the recovery and leads to the second rise in investment. This story is precisely characterized by four thresholds in average quality, which delineate the state spaces into five regions: initial credit freeze, unscreened credit with high interest rates, second credit freeze, screened credit, unscreened credit with low interest rates.

I make two extensions to the baseline model. In the first extension, I show that all results carry over to a framework with symmetric learning, in which neither borrowers nor banks know the true quality ex-ante. In this setup, endogenous exit induces the same counter-cyclical changes to the quality of the borrower pool. The second extension introduces bank capital and evaluates the effects of bank recapitalization policies. I show if high-quality borrowers rationally expect such recapitalization, they further postpone their investments. Thus, this type of policy, while widely used during the Great Recession, may have unintended consequences of hindering economic recoveries.

My model fits the cyclical patterns of bank lending standards and firm entry documented by existing studies. Moreover, I provide some new evidence on recovery duration and show they are consistent with the model. First, I show that recoveries after larger and longer-term booms are slower, and this pattern holds across different countries, as well as across different industries in the U.S. Second, I find that industries subjected to more varied bank screening effort during a typical recession recover significantly later. Screening effort in this case is proxied by the fraction of banks' collected financial reports that are of high quality (Berger et al., 2016; Lisowsky et al., 2016).

The rest of the paper is organized as follows. After the literature review in Section 2, Section 3 lays out the basic elements of the model, and Section 4 defines the equilibrium. Section 5 solves the model in closed form and constructs equilibria that resemble slow, fast, and double-dip recoveries. Section 6 provides empirical evidence, followed by two extensions discussed in Section 7. Finally, Section 8 concludes. The Appendix contains all the proofs and the details of the empirical analysis.

2 Literature Review

This paper contributes to several strands of literature. First, the paper is directly related to the theoretical works on banks' time-varying lending standards (Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Figueroa and Leukhina, 2015). My contributions to this literature are three-fold. (1) By extending the setup to a dynamic context, I am able to discuss recovery duration, which is the central object of this paper. (2) By introducing endogenous quality composition through borrower entry, I provide new and dynamic tradeoff regarding firms' investment timing choices. (3) While these papers study the causality of changes in macroeconomic conditions on bank lending standards, my paper, in accordance with Rajan (1994), argues that bank lending standards actually create low frequency business cycles. In fact, empirical papers (Bassett et al., 2014; Lown and Morgan, 2006;

Vojtech et al., 2016) have shown that bank lending standards can predict macroeconomic variables including investment and output.

More broadly, my paper relates to the literature on time-varying credit policies (Bernanke and Gertler, 1989; Holmstrom and Tirole, 1997; Kashyap and Stein, 2000), which mainly study variations in credit *quantity*. In these models, the wealth distribution among heterogeneous agents is crucial for equilibrium outcomes. However, prior to the 2007-2009 crisis, loan officers have almost never cited bank's capital position–a proxy for banks' net worth–as an important reason for adjusting lending standards (Bassett et al., 2014). This paper shuts down channels related to the net worth of banks and firms. Instead, it focuses on the composition of the borrower pool that determines the amount of credit and other equilibrium outcomes. In other words, time-varying credit *quality* drives changes in credit quantity. This paper predicts credit quality to be counter-cyclical, as confirmed in several empirical studies (Becker et al., 2015; Zhang, 2009; Greenwood and Hanson, 2013; Kaplan and Stein, 1993; Becker and Ivashina, 2014).

Firm births account for a significant portion of aggregate fluctuations in the U.S. economy, and their initial financing comes mostly from bank debt (Robb and Robinson, 2012; Fracassi et al., 2016). Using data from 22 OECD countries, Koellinger and Thurik (2012) find that fluctuations in entrepreneurship–measured by the share of business owners in the total labor force–are a leading indicator of the business cycle. Consistent with my model's predictions, business entry is pro-cyclical while entry quality is counter-cyclical (Lee and Mukoyama, 2015; Moreira, 2015; Ates and Saffie, 2014). Clementi and Palazzo (2016) construct a model that also replicates the above facts. In their model, entry selection occurs because firms' growth prospects vary over the business cycle. They show how entry and exit amplify aggregate TFP shocks through the evolution effect of new entrants, and how a negative entry shock can quantitatively explain the slow recovery from the Great Recession. By emphasizing variations in the prospect of financing, my paper introduces an alternative mechanism. This mechanism is also supported by Cetorelli (2014), which shows negative credit supply shocks select entrepreneurs with higher quality.

On the theory side, this paper follows the emerging literature on dynamic adverse selection, which typically assumes an exogenous news arrival process (Daley and Green, 2012). My paper endogenizes the sources of news as banks' screening decisions. It is closest to Zryumov (2014), which applies a similar setup to study early stage financing and private equity buyouts. In Zryumov (2014), recoveries are always instantaneous, driven by the assumption that low-quality borrowers still have *positive* NPV projects. Therefore, separating offers can exist in equilibrium. In my paper, it is exactly the opposite assumption–low-quality borrowers always have *negative* NPV projects–that eliminates the possibility of separating offers and drives slow recoveries. Moreover, by endogenizing the news process, my paper can generate double dips and episodes during which the market completely collapses.

3 The Model

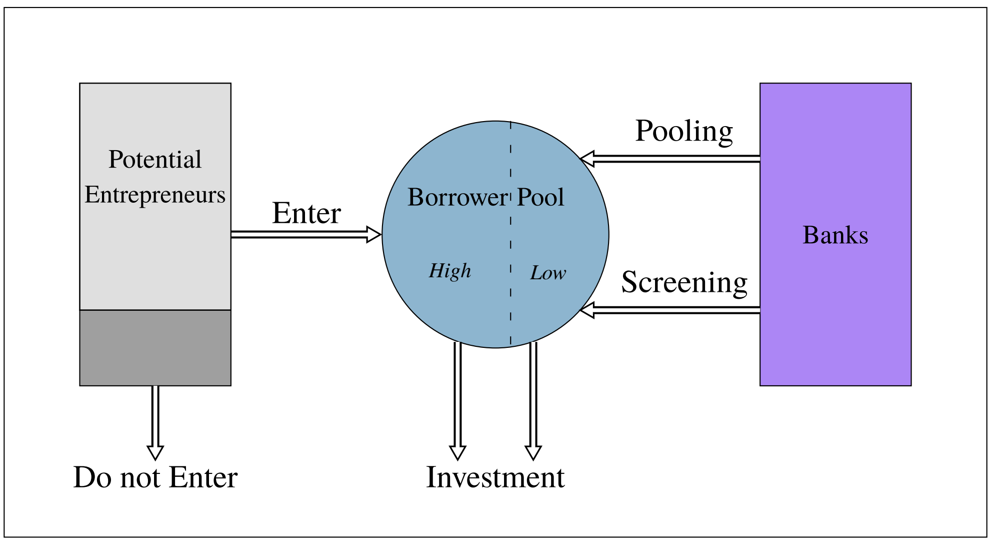

Figure 1 Model Overview

In this section, I construct an infinite-horizon model in continuous time. Figure 1 lays out the building blocks. The economy is populated with three groups of agents who are risk neutral and have the same discount rate ρ. *Entrepreneurs* have private information about the quality of their projects and need to borrow the entire investment amount from *banks*. Below I will use firm, borrower, and entrepreneur interchangeably. They all refer to agents who are already in the funding market. Banks may issue two types of loans. They can make pooling offers or screen borrowers and make separating offers. The equilibrium depends crucially on the composition of the funding market, which in turn is endogenously determined by the entry decisions of *potential entrepreneurs*.

The sequence of events within each period dt is as follows. (1) Aggregate state for investment payoffs is realized. (2) Potential entrepreneurs arrive in the economy and decide whether to enter the funding market. (3) Borrowers and banks play a borrowing game. I will describe each event below in detail. Players and their strategies will be introduced alongside.

3.1 Aggregate State, Borrowers, and Private Information

Borrowers have no wealth. They each own a project that requires a fixed investment amount I and produces verifiable output R_t instantaneously upon investment. R_t–the aggregate state of the economy at time t–follows a Markov switching process with realizations $\{R_g, R_b\}$. The heuristic transition probabilities between two states are

$$\begin{bmatrix} 1-\chi_b dt & \chi_b dt \\ \chi_g dt & 1-\chi_g dt \end{bmatrix},$$

where χ_s is the arrival rate of state s. R_g and R_b capture states of the economy with high and low total factor productivity (TFP) levels. Recessions are modeled as transitions from R_g to R_b. Throughout the paper, TFP shock is the only exogenous shock.[5]

Firms are of either high or low quality. A simple way to model this heterogeneity is to assume that the amounts of liquidity needed to complete the project are different.[6] In particular, some firms are hit by a liquidity shock of size l after the initial investment I is made but before the output R_t is produced. Once hit by this shock, a firm can continue only if it finds funds to defray it; otherwise, it is liquidated with no value. Below, I refer to those firms with and without liquidity shocks as high- and low-quality firms respectively.[7] The liquidity shock is observable but non-verifiable, and its size satisfies $l < R_t$. Therefore, it is ex-post efficient to provide the additional liquidity. However, $I < R_t < I + l$ so that ex-ante, it is only socially efficient to finance high-quality entrepreneurs.[8]

[5]This shock can be alternatively understood as a demand shock or a shock to the discount rate. I do not take a stand on which shock drives the business cycle.

[6]In an alternative setup, I assume entrepreneurs differ in the probability of success and all results go through. I maintain the current setup to obtain closed-form solutions.

[7]There is no uncertainty on the need for this addition liquidity: low types always need it whereas high types never need it. However, I maintain the name "shock" as the uncertainty still exists from lenders perspectives.

[8]This shock is the mirror image of Holmstrom and Tirole (1998). In Holmstrom and Tirole (1998), the problem is how to design a mechanism under which liquidity provision can avoid excessive liquidation to borrowers whose

Let $\mathcal{I}_t$ be the set of entrepreneurs who are already in the market at time t. Borrower i has two pieces of private information. First, he knows his time of entry, t^i. Second, and more importantly, he knows whether his project will require the additional liquidity l. Let $\theta \in \{h, l\}$ be the type of project. Below I refer a borrower with a type θ project to as a type-θ borrower. For the rest of this paper, I omit the superscript i and only use θ to differentiate borrowers.[9]

3.2 Firm Entry and Average Quality

Let n_t^h and n_t^l be the total measure of borrowers in the lending market at time t that are of high and low quality, and let $N_t = n_t^h + n_t^l$ be the total measure of all current borrowers. Define $\mu_t = \frac{n_t^h}{N_t}$ as the *average quality* of the borrower pool at time t, which is endogenously determined by firm entry on both the extensive and the intensive margins.

On the extensive margin, potential borrowers of dt order continuously arrive in the economy. They can choose to enter and start a business or forego the non-recallable opportunity. For tractability reasons, I assume that a total measure of $\eta N_t dt$ are of high quality, where η approximates the growth rate of the economy.[10] Meanwhile, the total measure of potential low types equals $\frac{1-\underline{q}}{\underline{q}}\eta N_t dt$, which implies that the average quality of potential borrower is $\underline{q}$. In equilibrium, $\underline{q}$ will be the lowest quality that the market may ever attain.

New borrowers can choose to enter the market by paying a cost.[11] High types' entry benefits are so large that cost will not matter for their decisions. For simplicity, I assume that they have zero cost and thus will always enter.[12] Among low types, $\frac{1-\bar{q}}{\bar{q}}\eta N_t dt$ also have zero cost, and the rest face a constant cost c. Here, $\bar{q}$ captures the highest quality that the market may ever attain, and the average quality in equilibrium varies between $\underline{q}$ and $\bar{q}$. For the rest of this paper, I refer to borrowers with entry cost c as high-cost candidates, and those with zero cost as low-cost candidates. If only low-cost candidates enter, *marginal quality*–defined as the average quality of entrants–is $\bar{q}$.

projects have positive NPV overall.

[9]Omitting the superscript i is $w.l.o.g.$ since in equilibrium, all borrowers of the same type take the same actions almost everywhere.

[10]If information is perfect so that only high type projects are funded, η is indeed the equilibrium growth rate.

[11]This cost can be interpreted as general setup costs for businesses that might include market investigations and pilot experiments.

[12]The results of this paper continue to hold if high types have the same cost structure as low types.

Marginal quality drops to $\underline{q}$ if all candidates enter.[13]

On the intensive margin, I assume that existing firms immediately receive a new project of the same quality after their current project is financed. The new project is managed by a new entrepreneur who spins off from the old managerial team. Meanwhile, the old entrepreneur exits the lending market once his project gets financed. As a result, each entrepreneur only aims to maximize the payoff from his own project. In addition, I assume that the relationship between bank and borrower breaks up after each transaction. This assumption eliminates the need to keep track of the borrower's personal history.

With entry on both margins, the average quality μ_t evolves continuously.

Maximization Let V_t^θ be the continuation payoff at time t to a type-θ borrower who has already paid the entry cost, $\theta \in \{h, l\}$. I will formally define V_t^θ in the next subsection after introducing the borrowing game. Low-cost candidates always enter. High-cost ones enter if the entry benefit V_t^l exceeds the entry cost c. The evolution process of μ_t depends on their entry decisions. If all candidates enter,

$$d\mu_t = \eta \left(1 - \frac{\mu_t}{\underline{q}}\right) dt. \tag{1}$$

If only low-cost candidates enter,

$$d\mu_t = \eta \left(1 - \frac{\mu_t}{\bar{q}}\right) dt. \tag{2}$$

3.3 The Borrowing Game

Upon entry, entrepreneurs play a borrowing game with lenders every period. Lenders in this game are banks. I model a competitive banking sector, and each bank has a perfectly elastic supply of capital. As a result, banks are willing to make loans as long as they expect to break even. Throughout the paper, these loan offers are assumed to be private and observed only by the associated bank and the borrower. The assumption on private offers is consistent with the fact that an individual borrower, in general, applies to multiple banks, and each single bank does not observe the bargaining and negotiation between its applicants and other banks before the loan actually gets

[13]The assumption that low-type candidates have heterogenous cost structure is not essential. In particular, all results go through if $\bar{q} = 1$.

issued.

Banks are ex-ante uninformed: they observe neither the type of a specific borrower nor the time he entered the market, but they know the distribution of borrowers in the market, characterized by μ_t. In equilibrium, μ_t is also the belief they assign to an unknown borrower.[14] While banks are ex-ante uninformed, they can become ex-post informed.[15] Each bank is endowed with a screening technology that enables it to exert effort s and learn the true type of a borrower with Poisson intensity s. Note that I depart from existing studies on bank screening by assuming that information arrival takes time. In reality, loan officers collect soft information over time through frequent and personal contacts with the borrower. Despite taking time, screening produces perfect information, i.e., information arrival fully reveals a borrower's type.[16] Banks are allowed to change screening effort every period. By choosing effort s, a bank incurs a flow cost $\kappa(s)\,dt$.

Within every period dt, borrowers play a borrowing game with banks. The game lasts for three stages (Figure 2), and each borrower is allowed to switch banks across periods. In Stage 1 (S1), each borrower applies to one bank for screening, and banks screen borrowers by choosing effort s_t. The action of applying for screening is not publicly observable.[17] In S2, screening either produces perfect information on the borrower's true type–screening "succeeds"–or produces no information at all–screening "fails". The screening outcome is private and only observable to the associated bank. Thus, it cannot be contracted on ex-ante.[18] In S3, all banks simultaneously make offers to all borrowers. Among these offers, those from the bank that a borrower has applied for screening

[14] This assumption is made $w.l.o.g.$ since the borrower is allowed to switch banks each period. I verify the belief is rational in equilibrium. Informally, in good times, all borrowers always receive funding instantaneously, and thus in equilibrium, time on the market is almost surely zero. In bad times, borrowers may wait and get screened. However, they always switch to a different bank each period since longer time in the market actually hurts them, as the average quality improves over time.

[15] I follow the literature by assuming that banks are unique information producers (Boyd and Prescott, 1986).

[16] I assume that banks have a small probability π of making a type II error so that low-type borrowers may be recognized as high type. Therefore, they will apply for being screened by a bank. The main results of this paper are derived based on $\pi = 0$. When $\pi = 0$, low types are indifferent between applying or not since there is no cost associated with applying for being screened. However, they must apply in equilibrium since otherwise banks cannot commit to screening afterwards.

[17] This assumption is made purely for consistency because otherwise all banks can observe the borrower's time on the market. A weaker assumption is that the application is publicly observed but only remembered until the end of the same period.

[18] All results go through if the screening outcome is publicly observable. In particular, low types still apply for screening since a successful screening takes time, and if they do not apply, banks immediately know that they have low quality.

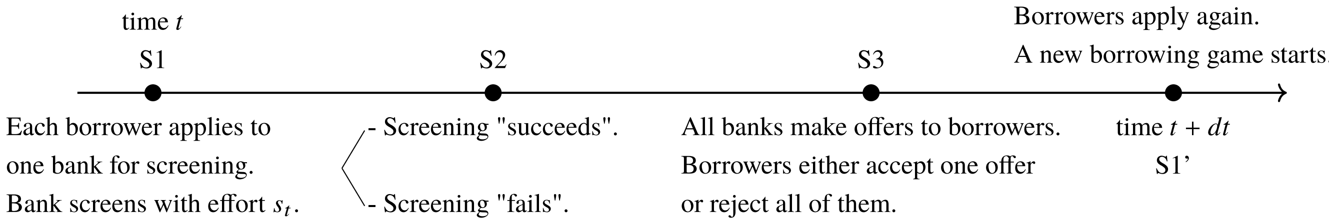

Figure 2 Timing of The Borrowing Game within dt

may contain more information from the screening outcome, whereas offers from other banks do not. Among the received offers (if any), borrowers either accept one or reject all of them. If an offer is accepted, investment I is made, liquidity shock l hits low types, and the final output R_t is produced conditional on the additional funding (if needed) being satisfied. If the borrower has rejected all offers or has not received any offer to begin with, he can apply again in the next period (S1'). Equivalently, he *waits* for the borrowing game in the next period. Below I explain each stage backwards in detail, starting with S2 and S3.

S2 and S3 All banks are allowed to make offers in S3. I first analyze the offer from a bank that the borrower has applied for screening. Obviously, this offer depends on the screening outcome in S2. In the case that screening has produced information, the bank is informed and simultaneously makes offers to the borrower with other uninformed banks. While being informed, it has bargaining power β over the borrower's profits, where $\beta \in (0, 1)$. Obviously, an informed bank will only make offers to borrowers with profitable investment potentials. If the borrower turns out to be low-type, the bank's screening effort is in vain. If, however, the borrower turns out to be high-type, the extracted profits depends on the high type's outside option: he either accepts a pooling offer (if any) from other uninformed banks, or waits for the borrowing game in the next period. Below, I will refer to the informed offers to high types as screened offers. They can be interpreted as lending on soft information.

In the case that screening has produced no information, this particular bank is no more informed than any other bank. Together, they can make uninformed pooling offers to all borrowers in the lending market. In this case, banks do not have any more information beyond μ_t, the average market quality. In equilibrium, if high-quality wait across periods, that is, they reject pooling offers and apply again in the next period, these offers will not be made by any bank in S3. When banks make uninformed pooling offers, they can be broadly interpreted as any institution who lends based on hard information (Petersen, 2004).

S1 In S1 when banks make decisions on screening effort s_t, they expect profits if screening produces information and the borrower turns out to be a high type. Meanwhile, screening incurs a flow cost $\kappa(s_t)\,dt$. This cost can be understood as the expense from background checks, auditing, or due diligence. The optimal screening effort maximizes the expected profits net the screening cost.

Maximizations As stated before, V_t^θ is the entry benefit in the potential borrower's problem. It is also the continuation payoff of a type-θ borrower at time t. His problem is to select an optimal stopping time T_t^θ, given his information set, and his expectation of offer flows $\{F_\tau\}_{\tau\geq t}$ from both screening and pooling:

$$V_t^\theta = \sup_{T_t^\theta \geq t} E\left[e^{-\rho\tau}\left(R_\tau - F_\tau\right)\right]. \tag{3}$$

A bank's problem has three parts. First, consider the problem of a bank after screening has succeeded. Obviously, if the borrower is a low type, his loan application is turned down and he returns to the borrower pool. A high-type borrower, instead, bargains with the bank over the payment. Let F_s^θ be the contracted payment from a type-θ borrower to the informed bank.[19] The Nash Bargaining solution suggests

$$F_s^h = (1-\beta)\left(R_t - V_t^h\right) + \beta I, \tag{4}$$

and $F_s^l \equiv \infty$. I will simply use F_s to denote F_s^h for the rest of this paper. Let Π_t^h be the profits that the informed bank can extract from a high-type borrower. Simple calculations show that $\Pi_t^h = (1-\beta)\left[(R_t - I) - V_t^h\right]$.

Next, consider the problem of an uninformed bank. Let F_p be the contracted payment from

[19]To avoid cumbersome notation, I omit the time subscript t. This is $w.l.o.g.$ in the class of Markov Equilibrium with state variable μ_t. For the same reason, I also omit the time subscript t in defining F_p below.

pooling offers such that banks break even. Obviously,

$$F_p(\tilde{\mu}_t) = \begin{cases} I + (1 - \tilde{\mu}_t)\, l & \text{If } F_p(\tilde{\mu}_t) \leq R_t \\ \infty & \text{Otherwise,} \end{cases} \tag{5}$$

where $\tilde{\mu}_t$ is the average quality of borrowers who accept the offer immediately. Obviously, $\tilde{\mu}_t = \mu_t$ if all borrowers accept. If, however, some high-quality borrowers reject, $\tilde{\mu}_t < \mu_t$.[20] To simplify notation, let $\Psi_t(\mu_t) = R_t - F_p(\mu_t)$ be the continuation value from immediately accepting a pooling offer with payment $F_p(\mu_t)$. Meanwhile, let $p_t \in \mathbb{R}_t \cup \{\infty\}$ be the maximal rate of the pooling offer among all banks who proposed in S3. A finite p_t is equivalent to banks playing mixed strategies in issuing pooling offers. A standard argument from Bertrand Competition suggests that

$$\begin{cases} p_t = 0 & \text{if } t \notin supp\left(T_t^h\right) \\ p_t \in \mathbb{R}^+ \cup \infty & \text{if } \{t\} \subset supp\left(T_t^h\right) \\ p_t = \infty & \text{if } \{t\} = supp\left(T_t^h\right) \end{cases} \tag{6}$$

where $supp\left(T_t^h\right)$ denotes the set of candidate stopping times chosen by high types. Clearly, no bank is willing to make a pooling offer if high types never accept them ($p_t = 0$); at least one bank is willing to extend pooling offers immediately to all borrowers if high types strictly prefer accepting so ($p_t = \infty$). When high types are indifferent between accepting and waiting, however, any rate of pooling offer can be viable.

Finally, consider a bank's problem in choosing screening effort s_t. Expecting profits $\Pi_t = \mu_t \Pi_t^h$, the bank's choice s_t is determined by

$$\max_{s_t} \Pi_t s_t dt - \kappa(s_t)\, dt. \tag{7}$$

[20] While banks screen borrowers and finance high-quality ones after screenings produce information, they leave the remaining borrower pool contaminated since low-quality borrowers return to the pool. This is the standard cream-skimming effect (Bolton et al., 2016; Fishman and Parker, 2015; Broecker, 1990). In the current setup where screening produces information continuously, the degree of contamination is at dt order and thus completely disappears within the same period.

4 Equilibrium

The economy is characterized by two state variables: the level of TFP R_t and the average quality μ_t.

Definition 1. *A Markov Equilibrium* Φ *is a set of state processes* $\{R_t\}$ *and* $\{\mu_t\}$*, borrowers' decisions* $\left\{T_t^\theta : \theta \in \{h,l\}\right\}$*, banks decisions* $\left\{s_t, p_t, F_p, F_s\right\}$*, and the induced valuation processes* $\left\{V_t^\theta : \theta \in \{h,l\}\right\}$ *that satisfy:*

1. *Borrower Optimality:* T_t^θ *solves borrower's problem* (3) *for type* θ*,* $\theta \in \{h,l\}$*.*
2. *Bank Optimality:*
   - *(a) Screening:* s_t *solves banks' screening problem* (7) *and* F_s *satisfies* (4)*.*
   - *(b) Pooling:* p_t *satisfies* (6)*, and* F_p *satisfies* (5) *if among borrowers with* $T_t^\theta = t$*, the average quality is* $\tilde{\mu}_t$*.*
3. *Entry Optimality: high-cost candidates enter if and only if* $V_t^l \geq c$*.*
4. *Market Clearing:* $V_t^h \geq \Psi_t^h$*.*
5. *Belief Consistency:* μ_t *is consistent with Equation* (1) *and* (2) *induced by entry decisions.*

Conditions 1-5 are standard. Market clearing, Condition 4, requires high-quality borrowers' continuation value to be at least the value of accepting an immediate pooling offer. Note that there is no such condition for low-quality borrowers, due to the assumption that their projects have negative NPV.

Theorem 1. *There exists an equilibrium.*

Proof. The equilibrium with exogenous screening is obtained by combining the proof of Proposition 1 and 2. The equilibrium with endogenous screening is obtained by combining the proof of Proposition 1 and 3. □

5 Solution

In this section, I show how equilibrium solutions generate slow, fast, and double-dip recoveries. Specifically, I isolate the effect of firm entry and bank screening. In Section 5.1, I assume that banks screen borrowers with a constant effort s^*, and show how recoveries can be slow or fast. In Section 5.2, I bring back banks' endogenous screening decisions and show how recoveries can have double dips.

Before preceding, I introduce the following parametric assumptions.

Assumption 1.

$$
\begin{aligned}
R_g - \left[I + \left(1 - \underline{q}\right) l\right] &< c && (8)\\
R_b - \left[I + \left(1 - \bar{q}\right) l\right] &> c && (9)\\
\frac{\chi_g}{\rho + \chi_g}\left(R_g - I\right) &< c && (10)\\
\frac{\beta s^*}{\rho + \beta s}\left(R_g - I\right) &< c && (11)\\
\chi_g\left(R_g - R_b\right) + \left(\beta s^* + \frac{\eta}{\bar{q}}\right)\left(R_b - I - c\right) &> \eta l\left(\frac{1}{\bar{q}} - 1\right) + \rho c && (12)\\
\left(\rho + \beta s^* + \chi_g\right)\Psi_b^h(\mu) - \beta s^*\left(R_b - I\right) &> \chi_g \Psi_g^h(\mu)\,. && (13)
\end{aligned}
$$

Condition (8) says in the good state, high-cost candidates will not enter if the quality has declined to $\underline{q}$. Likewise, (9) says they will enter in the bad state if the quality has risen to $\bar{q}$. Let

$$
\begin{aligned}
\mu_g^E &= 1 - \frac{R_g - I - c}{l}\\
\mu_b^E &= 1 - \frac{R_b - I - c}{l}.
\end{aligned}
$$

Clearly, the average market quality $\mu_t \in \left[\mu_g^E, \mu_b^E\right]$. Condition (10) guarantees that borrowers will never enter the market in state b just to wait until state g arrives. While (11) disincentivizes borrowers to wait in state g, (12) and (13) require high types to wait in state b if the market quality has dropped to μ_g^E, but not if the quality has increased to $\bar{q}$.

5.1 Slow and Fast Recoveries

In this section, I study the equilibrium when screening effort is assumed to be fixed at a constant level: $s_t = s^*$. This assumption captures the case that screening certain groups of borrowers could be costless, or that regulators can impose and monitor banks' effort in screening. The equilibrium has the following properties: 1) When $R_t = R_g$, pooling offers are always made, and all borrowers accept immediately. If the good state persists, the average borrower quality μ_t deteriorates. 2) When $R_t = R_b$, there exists a cutoff value μ_b^* such that, high-type borrowers would rather wait if and only if $\mu_t < \mu_b^*$. If the bad state persists, the average borrower quality μ_t improves.

State g: Booms

State g captures economic booms, i.e., states with high levels of TFP. Proposition 1 describes the equilibrium in state g.

Proposition 1. *When $R_t = R_g$, $\forall \mu_t \in \left[\mu_g^E, \mu_b^E\right]$*

1. *All borrowers immediately accept pooling offers $F_p(\mu_t)$ and their value functions are $V_g^\theta(\mu_t) = \Psi_g^\theta(\mu_t)$.*
2. *Banks make pooling offers at $F_p(\mu_t)$ with rate $p = \infty$.*
3. *The average quality μ_t satisfies $d\mu_t = \eta\left(1 - \frac{\mu}{\underline{q}}\right) dt < 0$ if $\mu_t > \mu_g^E$.*

Proof. See Appendix A.1. □

When the state is good, all borrowers accept pooling offers immediately, and banks also issue them immediately. Consequently, all low-type potential entrepreneurs enter the market, and the borrower pool deteriorates as the good state persists. During the boom period, unscreened credit is the dominant financing method,[21] and bank lending standards are low. Below I provide a heuristic proof.

Since low-type borrowers' projects are of negative NPV, imitating high-type borrowers is the only way to receive funding. As a result, low-type borrowers have to wait if their high-type

[21]Within any period dt, borrowers who receive screened credit are of measure zero.

counterparts do so. In addition, banks will never issue pooling offers if they expect high-type borrowers to wait. Therefore, high-type borrowers' waiting incentives determine the equilibrium strategies of all agents (Hellwig, 1987). A simple cost benefit analysis reveals that the incentive to wait is low when $R_t = R_g$. In state g, delaying investment is costly since investment return R_g is high. Meanwhile, all potential borrowers enter the market, and the pool deteriorates. In addition, the bad state in which borrowers are further worse off may arrive. The only benefit of waiting is bank screening, which is maximized at $\mu_t = \underline{q}$. Under (11), this benefit is dominated by waiting cost even at $\mu_t = \underline{q}$. Note if banks' screening effort $s^* = 0$ so that there is no benefit of waiting, Condition (11) is automatically satisfied.

State b: Recovery Shapes

State b, states with low levels of TFP, captures recessions and the subsequent recoveries. Proposition 2 is the main result of this section.

Proposition 2. *When $R_t = R_b$, assume $\chi_g \left(R_g - R_b\right) + \beta s^* \left(R_b - I\right) \leq \left(\rho + \beta s^*\right) c$, there exists a unique μ_b^**

1. *Waiting region: for $\mu_t \in \left[\mu_g^E, \mu_b^*\right)$, high-type borrowers wait. Only high-type borrowers are financed with screening offers. Investment is delayed.*
2. *Pooling region: for $\mu_t \in \left[\mu_b^*, \mu_b^E\right]$, all borrowers immediately accept pooling offers $F_p\left(\mu_t\right)$. Investment is not delayed.*

Proof. See Appendix A.2. □

Appendix A.2 describes the extended version of Proposition 2, where the condition $\chi_g \left(R_g - R_b\right) + \beta s^* \left(R_b - I\right) \leq \left(\rho + \beta s^*\right) c$ is relaxed. Intuitively, this condition requires the entry cost c to be sufficiently large that high-cost candidates will not enter at $\mu_t = \mu_b^*$. The results only differ quantitatively if the condition is violated. Below I provide a herustic proof to Proposition 2 and explain the intuition alongside.

While the key analysis is again high types' incentive to wait, the costs and benefits are different from those in state g. First, investment delay is less costly since $R_b < R_g$. Second, since $\mu_t < \mu_b^E$, high-cost candidates do not enter the market and thus, the borrower pool improves over time. Third, by waiting, a high-type borrower increases the chances that he may be verified by a bank. Lastly, the good state may arrive, in which borrowers are better off. Condition (12) guarantees that he strictly prefers waiting when $\mu_t = \mu_g^E$. Thus, a waiting region exists. Let $W_b^\theta(\mu_t)$ be a type-θ borrower's continuation value of waiting. By considering high and low types' continuation value over a small time interval $[t, t+dt]$, I derive the following Hamilton-Jacobi-Bellman (HJB) Equations:

$$\left(\rho + \beta s^* + \chi_g\right) W_b^h = \left(W_b^h\right)' \eta \left(1 - \frac{\mu}{\bar{q}}\right) + \beta s^* (R_b - I) + \chi_g V_g^h \tag{14}$$

$$\left(\rho + \chi_g\right) W_b^l = \left(W_b^l\right)' \eta \left(1 - \frac{\mu}{\bar{q}}\right) + \chi_g V_g^l. \tag{15}$$

The right-hand-side of Equation (14) describes high-type borrowers' benefits of waiting. The first term comes from entry, which improves average quality μ_t. The second term derives from bank screening, which accrues β fraction of the total surplus from a successful screening to the high-type borrower. In this case, high types' outside option equals W_b^h, which is the continuation value from waiting. The last term accounts for the possibility that the state switches and a boom arrives. Equation (15), low-type borrowers' HJB can be decomposed similarly. Note that the benefit from bank screening does not accrue to these borrowers.

As μ_t increases, the incentive to wait decreases for two reasons. First, the surplus from being verified as high type decreases since the outside option–accepting an immediate pooling offer–increases. Second, an examination of Equation (2) shows that the marginal improvement gets lower as μ_t itself increases. Otherwise, the process of μ_t will explode. Therefore, there exists a threshold μ_b^* such that the high-type borrower is indifferent between waiting and accepting a pooling offer $F_p\left(\mu_b^*\right)$. μ_b^* is determined by two boundary conditions. First, the value-matching condition (16) holds, and the borrower is indifferent between waiting and accepting. Second, since μ_b^* is optimally chosen by high-type entrepreneurs, the smooth-pasting condition (17) is also necessary.[22]

$$W_b^h\left(\mu_b^*\right) = \Psi_b^h\left(\mu_b^*\right) \tag{16}$$

$$\left(W_b^h\right)'\Big|_{\mu=\mu_b^*} = \left(\Psi_b^h\right)'\Big|_{\mu=\mu_b^*} \tag{17}$$

[22]See Proposition 6.2 of Stokey (2008) for an analog.

Lemma 1 presents the solution to μ_b^*.

Lemma 1. *There exists a unique μ_b^* that satisfies both the value-matching and smooth-pasting conditions:*

$$\mu_b^* = \frac{\chi_g \left(R_g - R_b\right) + l\left(\beta s^* + \eta\right) + \rho\left(I + l - R_b\right)}{l\left(\rho + \beta s^* + \frac{\eta}{\bar{q}}\right)}.$$

Proof. Apply Condition (16) and (17) to HJB (14), the equation reduces to one linear in μ_b^*. The solution follows easily. □

Corollary 1 shows some important comparative static results of μ_b^*.

Corollary 1. *μ_b^* increases with s^* and η.*

Proof. Obvious from Lemma 1. □

Intuitively, high-type borrowers wait longer if they know banks are screening with higher intensity (higher s^*). This result is important for understanding double-dip recoveries in Section 5.2. Likewise, borrowers also wait longer if they know the pool improves at a higher rate (higher η). This result helps us understand the extended version of Proposition 2, elaborated in Appendix A.2.

Transition Dynamics: Slow versus Fast Recovery

In this section, I study transition dynamics over the business cycle. Define *recovery* as the first time when output exceeds its pre-recession level if there is no further shock to TFP. I will show that recoveries may be slow or fast, depending on the average quality at the onset of the recession, which in turn is determined by the size and duration of the preceding economic boom.

Consider an economy in a boom ($R_0 = R_g$) and that the average quality starts at $\mu_0 = \mu_b^E$. All borrowers immediately accept pooling offers, and all potential entrepreneurs enter. As the boom persists, the average quality μ_t continues to decline, illustrated by the top axis of Figure 3. If the boom is large and has persisted for a sufficient amount of time, the average quality μ_t becomes lower than μ_b^*. When a bad shock finally hits (the vertical dashed arrow), high-type borrowers prefer to wait, and only screening offers are made. Lending standards are high during this period since credits are rationed. Investment is thus delayed, and output falls dramatically; the patterns of macroeconomic variables represent that in a slow recovery. In contrast, following a short and/or small boom, the drop in μ_t is only moderate (the vertical dashed arrow in Figure 4), and the average quality μ_t still exceeds μ_b^*. After the same bad shock, lending standards are unchanged, no investment is delayed, and macroeconomic variables represent that in a fast recovery.

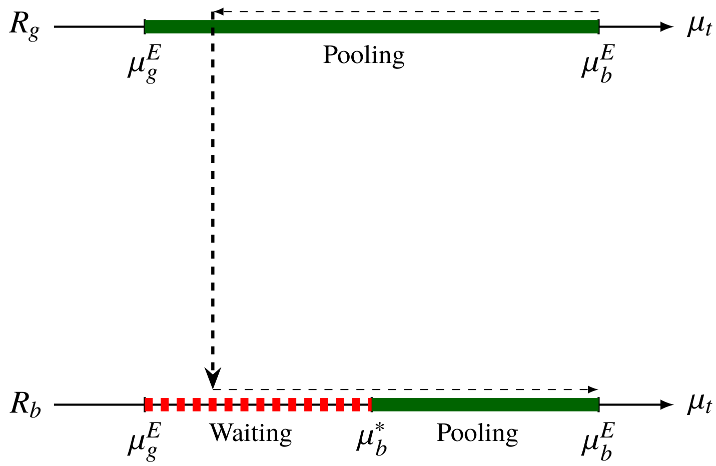

Figure 3 Transition Dynamics in a Slow Recovery

This figure shows transition dynamics in a slow recovery. The top (bottom) axis depicts the state space $\left(R_t \in \left\{R_g, R_b\right\}, \mu_t \in \left[\mu_g^E, \mu_b^E\right]\right)$. The economy starts with $R_t = R_g$, and μ_t decreases as R_t stays unchanged. When $R_t = R_g$ has persisted sufficiently long, μ_t falls below μ_b^*, and a slow recovery follows when R_t drops to R_b.

According to Equation (14), μ_g^E decrease with R_g. Moreover, the decline in μ_t is larger if the economy has spent longer time in state g. Corollary 2–the main hypothesis for empirical analysis in Section 6.2–naturally follows.

Corollary 2. *Slow recoveries are likely to follow large and long-term economic booms.*

Numerical Illustration

Figure 5 plots the typical shapes of both high (top panel) and low types' (bottom panel) continuation value from waiting and accepting an immediate pooling offer. The horizontal axis is the state variable μ_t. The blue solid curves describe the continuation value functions from waiting, and the slopped dashed line, as references, plot $\Psi_b^\theta(\mu)$–the payoff functions from accepting an

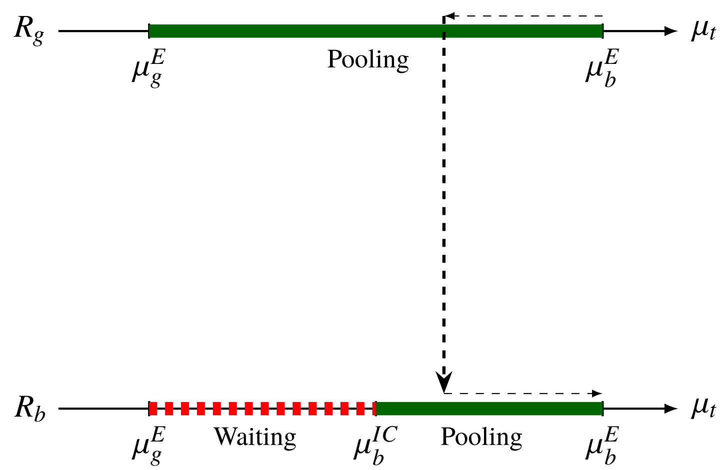

Figure 4 Transition Dynamics in a Fast Recovery

This figure shows transition dynamics in a fast recovery. The top (bottom) axis depicts the state space $\left(R_t \in \left\{R_g, R_b\right\}, \mu_t \in \left[\mu_g^E, \mu_b^E\right]\right)$. The economy starts with $R_t = R_g$, and μ_t decreases as R_t stays unchanged. If $R_t = R_g$ has not persisted sufficiently long, μ_t still lies above μ_b^*, and a fast recovery follows when R_t drops to R_b.

immediate pooling offer. The vertical dashed line marks the boundary μ_b^*, which separates the state space into the waiting region (left) and the pooling region (right). In this case, μ_b^* equal 0.75. Accepting a pooling offer guarantees a higher continuation value when $\mu > \mu_b^*$. When $\mu < \mu_b^*$, however, the top panel shows that waiting is more beneficial to high types (but not necessarily to low types).

Simulation I simulate the economy for 100 periods and generate scenarios similar to both slow and fast recoveries. Figure 6 plots the simulated investment and output processes in both a slow recovery and a fast one, left and right panel respectively. Both economies start in a boom with $\mu_0 = \mu_b^E$. While recession occurs in period 21 in the left economy, the same bad shock hits the right economy much earlier, in period 6.

The solid curves plot the simulated investment and output. Indeed, the right economy bounces back right after the recession whereas in the left economy, there exists a significant period during which both investment and output are below their pre-recession levels.[23]

[23]Many discussions on recovery have focused on both the level and the growth rate of the output post the recession (CBO, 2012; Summers, 2016). While levels of a slow and a fast recovery are dramatically different under the current model setup, the growth rates are more or less the same ($\approx \eta$). However, one can easily get the slope difference by assuming that η increases with the measure of borrowers who actually obtain financing.

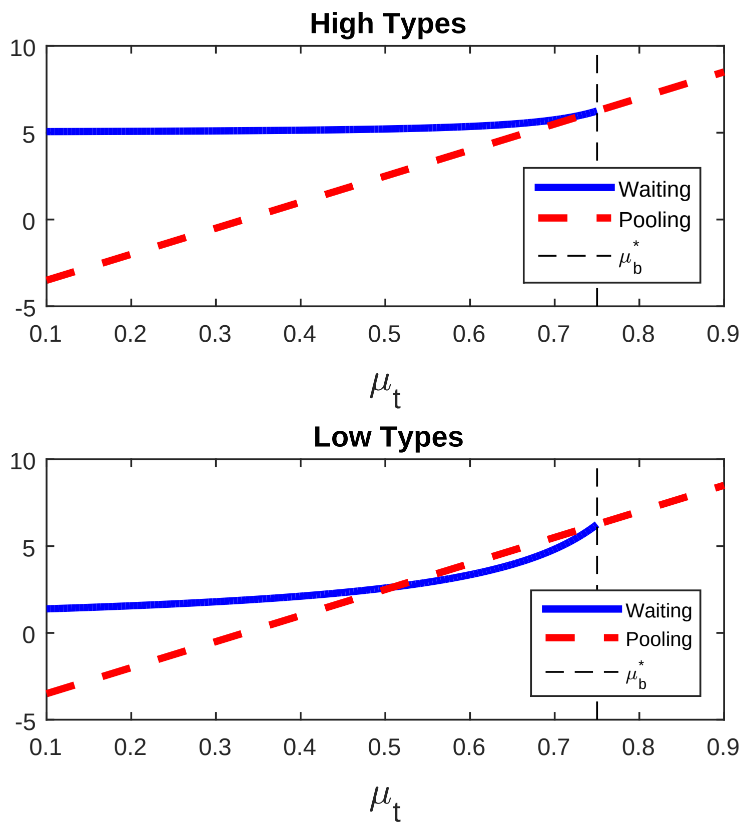

Figure 5 Value Functions in State b.

This figure shows high- and low-quality borrowers' value functions when $R_t = R_b$. In both panels, the horizontal axes represent μ_t–average borrower quality in the market. The blue curve depicts W_b^θ, the continuation value if the type-θ borrower wait. The red, dashed curve plots the continuation value from immediately accepting a pooling offer at face value $F_p(\mu)$. μ_b^* is the cutoff value above which a high-quality borrower is willing to take pooling offers. The parameter values are $I = 20$, $R_g = 35$, $R_b = 30$, $l = 15$, $c = 20$, $\beta = 0.5$, $s^* = 1$, $\rho = 0.5$, $\chi_g = \chi_b = 10^{-4}$, $\eta = 0.5$, $\bar{q} = 0.9$, $\underline{q} = 0.1$.

5.2 Double Dips

In this section, I endogenize banks' screening decisions and show how recoveries may experience double dips. In a double-dip recovery, the economy falls into recession, recovers with a short period of growth, then falls back into recession before it finally recovers.

Assumption 2. *1. Banks face binary screening choices, $s_t \in \{0, s^*\}$.*[24] *While low screening*

[24]The more general specification is $s_t \in \{\underline{s}, \bar{s}\}$, where $0 < \underline{s} < \bar{s}$. All results in this subsection carry over quantitatively. The only difference is screening offers will not completely disappear.

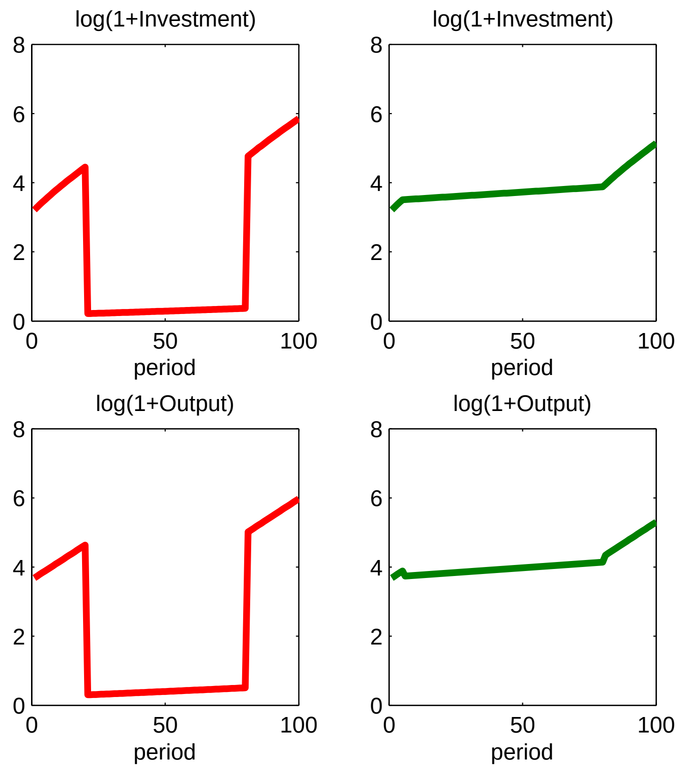

Figure 6 Simulation: Slow and Fast Recoveries

This figure shows the simulated investment and output in both a slow (left panel) and a fast recovery (right panel). Both economies start with $\left(R_t = R_g, \mu_t = \mu_b^E\right)$. R_t switches to R_b in period 21 in the top economy but in period 6 in the bottom economy. Therefore, both investment and output experience a sluggish period in the top economy but not the bottom one.

effort $s_t = 0$ incurs no cost, high screening effort $s_t = s^*$ incurs a constant flow cost $\kappa^* dt$.

2. $\frac{(1-\beta)l}{4} > \kappa^* > (1-\beta)\, l \max\left\{\mu_b^*\left(1-\mu_b^*\right), \mu^{SW} V_b^h\left(\mu^{SW}\right)\right\}$, *where* μ^{SW} *is the unique solution to* $W_b^h\big|_{s_t\equiv 0} = W_b^h\big|_{s_t\equiv s^*}$.

The first condition on binary choices is made purely for exposition convenience. In particular, the results continue to hold if s_t is modeled as a continuous choice. The second condition puts restrictions on κ^*. κ^* can not be too large. Otherwise banks always choose low screening effort, $s_t = 0$.[25] However, κ^* cannot be too small either. Otherwise, banks almost always chooses high

[25]In general, one can imagine that banks may costlessly screen borrowers with effort $\varepsilon > 0$ (low screening effort). This section takes $\varepsilon = 0$ $w.l.o.g.$ but keeps the name "low" effort. All results in this section go through if ε is small

screening effort s^*.

Let Assumption 1 continue to hold. The equilibrium in state g is thus unchanged. Below, I focus on the equilibrium outcomes in state b. Proposition 3 is the main result.

Proposition 3. *When $R_t = R_b$, there exists a unique quadruple $\left\{\mu_b^0, \mu_b^{dd}, \mu_b^s, \mu_b^*\right\}$.*

1. *First dip. If $\mu_t \in \left[\mu_g^E, \mu_b^0\right]$, high-type borrowers wait, and banks screen with low effort, $s_t = 0$. No loan is made, and the lending market completely collapses.*

2. *First rise. If $\mu_t \in \left[\mu_b^0, \mu_b^{dd}\right]$, pooling offers are made, all borrowers immediately accept them, and banks screen with low effort, $s_t = 0$. The lending market recovers temporarily.*

3. *Second dip*

   (a) *If $\mu_t \in \left[\mu_b^{dd}, \mu_b^s\right]$, high-type borrowers wait, and banks screen with low effort, $s_t = 0$. No loan is issued, and the lending market collapses again.*

   (b) *If $\mu_t \in \left[\mu_b^s, \mu_b^*\right]$, high-type borrowers wait, and banks screen with high effort $s_t = s^*$. Only screened loans are provided, and investment is delayed.*

4. *Second rise. If $\mu_t \in \left[\mu_b^*, \mu_b^E\right]$, pooling offers are made, and all borrowers immediately accept them. Both unscreened and screened loans are provided. The lending market finally recovers.*

Thus, if $\mu_t < \mu_b^0$ at the onset of a recession, the recovery experiences a double dip conditional on R_t staying unchanged.

Proof. See Appendix A.3. □

The equilibrium state space is divided by four thresholds. μ_b^0 and μ_b^* are the thresholds that high types would be indifferent between waiting and accepting a pooling offer, had screening intensity been fixed at 0 and s^* respectively. When μ_t increases to μ_b^s, banks switch from low to high screening effort. However, such transition is not smooth in the dynamic context. In particular, expecting the transition, high types start to wait at $\mu_t = \mu_b^{dd}$. Figure 7 provides a graphic illustration of the state space. Below I provide a heuristic proof.

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and positive. The only difference is that the market does not *completely* collapse as in Case 1 and 3(a) of Proposition 3. In these two cases, screened credit is provided at very low rate ε, which is even more consistent with the real world.

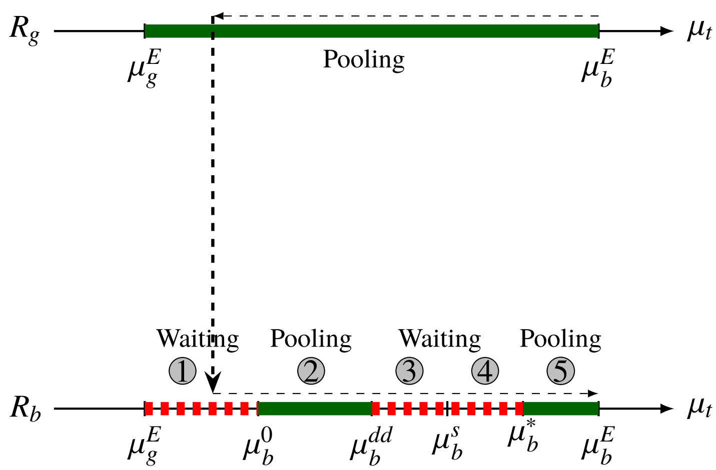

Figure 7 Transition Dynamics With Double Dips

This figure shows transition dynamics in a recovery with double dip. The economy starts with $\left(R_t = R_g, \mu_t = \mu_b^E\right)$ and μ_t decreases as the boom persists. If μ_t has fallen below μ_b^0 when R_t switches to R_b, a double-dip recovery follows. In Region 1-3, banks do not screen, $s_t = 0$ while they do screen $s_t = s^*$ in Region 4-5. High-quality borrowers wait in Region 1, 3, and 4 while they accept pooling offers in Region 2 and 5. The first dip occurs in Region 1, followed by the first rise in Region 2, the second dip in Region 3 & 4, and the second rise in Region 5.

Recall that the expected profits from banks are

$$\Pi\left(\mu_t\right) = \mu_t\left(1-\beta\right)\left[\left(R_t - I\right) - V_t^h\right].$$

Clearly, bank profits are low when the average quality μ_t is low: when the market is filled with low-type borrowers, the borrower being screened is likely to be of low quality, from whom the bank cannot make any profit. This necessarily implies that banks choose low screening effort, $s_t = 0$ for low levels of μ_t. Additionally, the comparative static results in Corollary 1 show μ_b^* increases in s^*. Thus, μ_b^*–the indifference threshold if bank screen with constant effort s^*–is higher than μ_b^0–the same threshold if they know banks screen with effort 0. Assumption 2 guarantees that banks switch to high effort as the average quality improves, and the switching threshold μ_b^s lies between μ_b^0 and μ_b^*.

The determinant for the recovery pattern still hinges on high types' incentive to wait. The analysis is similar to that in Section 5.1, except for the benefits of screening. With endogenous s_t, high types may or may not receive bank screening. If $\mu_t < \mu_b^s$, high types' waiting benefits do not include the benefit of being verified by banks. However, high-type borrowers still wait if μ_t is even below μ_b^0 since they expect the pool to improve. In this case, low screening by banks and waiting by high types lead to the collapse of the lending market. As μ_t increases to μ_b^s, banks start to screen, and waiting benefits now increase discontinuously: waiting not only leads to a better borrower pool, but also increases the prospect of being verified by a bank. Both screening and entry patterns offer high types dynamic reasons to wait.

When high-type borrowers expect banks to increase effort, they have an additional reason to wait. Indeed, when μ_t is only slightly below μ_b^s, high-type borrowers know that banks will put forth high effort very soon. Thus, they stop accept pooling offers and wait. This effect is captured by the boundary μ_b^{dd}. If the restrictions on κ^* in Assumption 2 fail, μ_b^{dd} could be less than μ_b^0, in which case the region for the first rise (Region 2) disappears. However, all other cases in Proposition 3 still exist. Thus, the broad lesson is endogenous screening can still lead to complete market collapse.

To summarize, if μ_t falls below μ_b^0 when a recession hits, banks do not screen initially, and knowing that, borrowers wait as they expect the borrower pool to improve. This constitutes the first dip (Region 1). During this period, the lending market completely breaks down, and lending standards are the highest: neither screening or pooling offer exists. Meanwhile, the borrower pool is improving. When the borrower pool has improved moderately, $\mu_t > \mu_b^0$, high-type borrowers start to accept pooling offers for two reasons. On one hand, the loan rate has been reduced due to entry. On the other hand, banks continue to be lazy and remain so during the short run–they are reluctant to screen with high effort as the expected profits are still below the screening cost κ^*. This leads to the first rise (Region 2). During this period, loans with very high interest rates are issued and accepted. Lending standards are loosen temporarily. As μ_t further increases to μ_b^{dd}, high-quality borrowers realize that banks will increase effort soon. Expecting that, these borrowers find it more beneficial to wait, which starts the second dip. The lending market breaks down again completely (Region 3). Finally, banks switch to high effort when μ_t reaches μ_b^s (Region 4). Screening offers are made. Borrowers who are not successfully screened, then, keep waiting until μ_t finally exceeds μ_b^*, after which the second rise follows (Region 5).

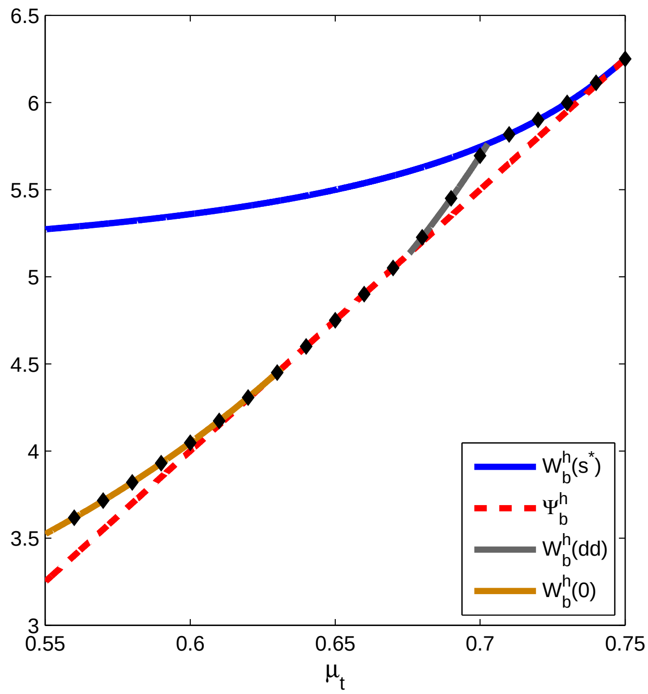

Figure 8 High-type Borrowers' Value Functions with Double Dips

This figure plots a high-quality borrower's value function when $R_t = R_b$, and s_t is endogenously chosen. The x-axis denotes μ_t–average market quality. The blue ($W_b^h(s^*)$) and brown ($W_b^h(0)$) curves represent the value of waiting for a pooling offer if $s_t \equiv s^*$ and if $s_t \equiv 0$. The grey ($W_b^h(dd)$) curve shows the waiting of waiting for bank switching from $s = 0$ to $s = s^*$. Again, the dashed red line is the value from accepting an immediate pooling offer.

Numerical Illustration and Simulation Figure 8 plots the typical shape of high-type borrowers' value function. The curve marked by scatterd diamonds represents the value function of high types. The state space for μ_t is divided into five regions. In Region 1, high-type borrowers obtain a higher continuation value by waiting ($W_b^h(0)$), as they expect the pool to improve due to entry. When μ_t exceeds μ_b^0, which equals 0.63 in this case, high-quality borrowers are happy to accept pooling offers and receive Ψ_b^h. However, expecting that banks will increase effort soon, these borrowers decide to wait again once μ_t exceeds $\mu_b^{dd} = 0.68$. In this region, borrowers expect $W_b^h(dd)$. This leads to the second dip. Indeed, banks switch to high effort when μ_t exceeds $\mu_b^s = 0.70$ and thus increase borrowers' payoff to $W_b^h(s^*)$. Finally, the second rise occurs in Region 5 ($\mu_t > \mu_b^* = 0.75$), and borrowers accept pooling offers.

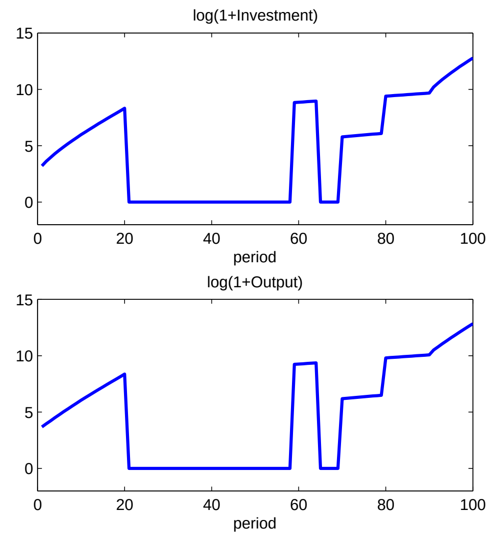

Figure 9 Simulation: Double-Dip Recessions

This figure shows the simulated investment and output in a double-dip recovery. The economy starts at $\left(R_0 = R_g, \mu_1 = \mu_b^E\right)$ and switches to $R_t = R_b$ in period 21. The first dip occurs between period 21 and 58, followed with a temporary rise between period 59 and 64, and a second dip between period 65 and 79. The second rise occurs after period 80.

Again, I simulate the economy for 100 periods. All parameters are identical to those in the last section. Figure 9 plots the simulated investment and output processes, as in a double-dip recession. The economy is in a boom from period 1-20, hit by a bad shock in period 21 and a good shock in period 91. Compared with the top panel in Figure 6, it is evident that there are two dips. In the first dip (period 21-58), investment and output both drop to zero. The economy picks up temporarily between period 59 and 64, with a second dip following after period 65. During this period, little investment and output are realized. It is not until period 80 that the economy finally recovers and exceeds the pre-recession level.

6 Empirical Analysis

In this section, I discuss the empirical relevance of both the mechanism and the results of the model. I start by citing existing evidence that is consistent with the model's key mechanism. In Section 6.2, I study the determinants of recovery duration and focus on the effects of boom duration, recession size, and bank screening.

6.1 Existing Evidence

1. Bank lending standards are counter-cyclical. This pattern has been confirmed in the U.S. (Asea and Blomberg, 1998; Lown and Morgan, 2006), as well as other countries such as Italy (Rodano et al., 2015). Figure 10 replicates this fact. In this figure, bank lending standards are measured by the percentage of loan offers who report a tightening in lending standards, collected from the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS).

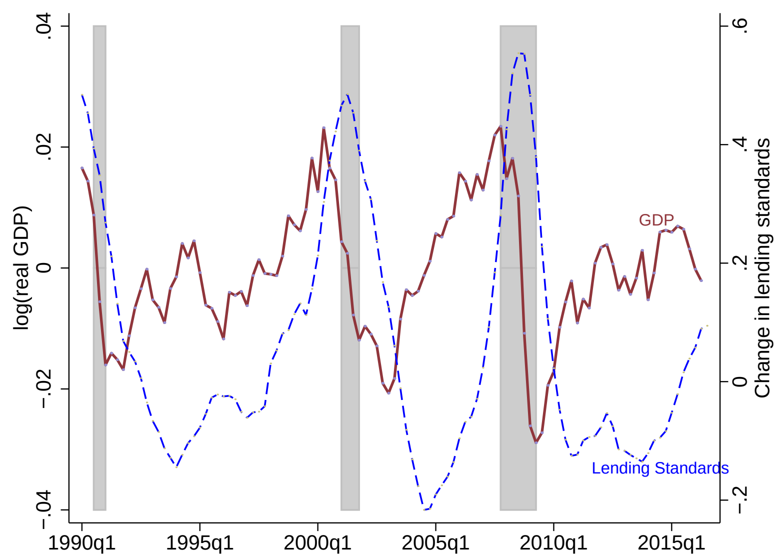

Figure 10 Lending Standards and Output

This figure plots the series of bank lending standards and output. The dashed curve depicts the sequence of bank lending standards, measured by the net percentage of loan officers who report a tightening in lending standards. The data are collected from Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). The solid curve shows output from Fernald (2012), measured as percentage change at an annual rate (=400×changes in natural log). Both sequences are further smoothed with moving-average filter with two lagged terms, three forward terms, and including the current observation in the filter. Shaded areas are recessions identified by the NBER.

2. Firm entry quantity is pro-cyclical while entry quality is counter-cyclical. Using data from the Annual Survey of Manufactures, Lee and Mukoyama (2015) find that entry rates of manufacturing firms are strongly pro-cyclical. However, plants entering in booms are about

10-20% less productive than those entering in recessions. Using data from the Longitudinal Business Database (LBD), Moreira (2015) finds a one percent increase in the cyclical component of output is associated with a 0.3 percent decrease in labor productivity of new firms. The results are robust to different measures of quality: productivity, probability of survival, and innovations. Ates and Saffie (2014) provide similar findings using data from Chile.

Figure 11 Firm Entry Rate and Output

This figure plots the series of firm entry rate and output. The dotted green curve depicts the sequence of firm entry rate, measured by the number of new firms over exiting firms. The data are collected from the Firm Characteristics Data Tables of the Business Dynamics Statistics (BDS). The solid curve shows output from Fernald (2012), measured as percentage change at an annual rate (=400×changes in natural log). The output sequences is further smoothed with moving-average filter with two lagged terms, three forward terms, and including the current observation in the filter. Shaded areas are recessions identified by the NBER.

3. Credit quality deteriorates during an economic boom. Loan delinquency rates begin to rise while the economy is still in booms (Figueroa and Leukhina, 2015). In addition, among loans that default *ex-post*, those originated in booms have lower realized recovery rates (Zhang, 2009).

4. Bank lending standards predict future macroeconomic outcomes. Bassett et al. (2014) find that tightening lending standards leads to substantial decline in output and the borrowing

capacity of businesses and households.[26]

6.2 New Evidence: Determinants for Recovery Duration

In this section, I study the determinants for recovery duration. In particular, I focus on the effects of boom length, recession size, and bank screening. The theoretical model predicts that larger booms which proxy further deterioration in borrower pool recessions will be followed by slower recoveries, and that more varied bank screening during recessions should predict slower subsequent recoveries. I show that these predictions are consistent with the data. Appendix B supplements the full analysis using several data sources. Below I briefly present the data and results.

Data Sources and Variable Definition

I use several data sets to conduct the analysis at country- and industry-level. For country-level tests, I construct two data sets: annual real GDP per capita from the Maddison project and quarterly real GDP for OECD countries. For industry-level tests, I obtain gross GDP for each industry in the U.S. from the Bureau of Economic Analysis (BEA). I remove the trends in all time series using standard filtering technique and define peak, trough, and recovery following the literature. Consistent with the model, recovery is defined as the first year (quarter) that output exceeds the pre-recession level. Boom length, recession size, and recovery duration are defined accordingly.

One additional data set from the Risk Management Association (RMA), enables me to measure bank screening at the annual industry level. Specifically, the RMA documents the number of different types of financial reports that its membership banks collect from borrowers across industries. Berger et al. (2016) and Lisowsky et al. (2016) provide a detailed introduction to the data set. These reports are classified by their quality into five categories–unqualified audit, review, compilation, tax return, and other. Noticeably, high-quality reports–unqualified audits in this case–contain not only borrowers' hard information such as tax returns, but also the relevant soft information such as

[26] Greenstone et al. (2014) use the LBD data and find that shocks to credit supply have little effect on employment. However, this finding is not inconsistent with my model, which emphasizes shocks from credit demand. The credit supply shock they emphasize stems from the bank balance sheet channel (Holmstrom and Tirole, 1997).

external auditor's opinion. Thus, the fraction of unqualified audits collected by banks is a nature proxy for screening effort in the empirical work.

Estimation Results

The empirical results are consistent with the model. Tests at the country level show that one more year spent in the boom delays the subsequent recovery by about 0.2 years, after controlling for the size of the recession. The effect is a bit smaller at the industry level: 0.16 years. Moreover, if the difference between bank screening in the recession year and the boom year increases by one standard deviation, the recovery is delayed by a period between 0.56 and 0.88 years. All results are significant and robust to different specifications. The results are consistent with those in Lisowsky et al. (2016).

7 Extensions

7.1 Symmetric Learning

The baseline model has assumed that entrepreneurs have private information on their projects. In reality, entrepreneurs and banks may be equally uninformed: neither party knows the true quality *ex-ante*, and they can both learn it *ex-post* through bank screening. In this section, I show that the main results continue to hold in this symmetric learning context. Thus, an econometrician cannot differentiate a private information model from one with symmetric learning.

To see this, let me make two modifications to the baseline model. First, while newly-born entrepreneurs still have on average quality $\underline{q}$, neither the bank nor the potential entrepreneur knows the true type. Below, I will call these borrowers *unknown* types. Second, besides the fixed entry cost c, potential borrowers face an additional time cost wdt: they receive wdt if they stay outside the funding market. wdt can be interpreted as working as contractors or employees. Under this setup, the state variable is the fraction of unknown borrowers in the economy. Let it be $\tilde{\mu}_t$. Suppose banks commit to constant screening policies. In booms with high TFP levels, an unknown borrower does not find it worthwhile to wait and thus always accepts a pooling offer. In busts, the equilibrium again depends on $\tilde{\mu}_t$. It is easily shown that there exists a unique $\tilde{\mu}_b^*$ such that borrowers wait if and only if $\tilde{\mu}_t \leq \tilde{\mu}_b^*$. Intuitively, with high c and low R_b, potential entrepreneurs will not enter the market in busts. Among those who are already in the market, a fraction $s^* dt$ of them learn their type during period dt. Conditional on the screening results, high types get their projects financed immediately, and low types exit to pursuit the outside option wdt. Since borrowers who have been financed immediately will receive an identical project (entry on the intensive margin), the borrower pool gets persistently improved. Thus, unknown-type borrowers will not accept a pooling offer until $\mu_t \geq \tilde{\mu}_b^*$. Finally, the result on double-dip recovery follows when banks endogenously choose screening. Note in this model, the time-varying quality of the borrower pool is driven by the ex-post choices by low-type borrowers–staying in booms and exiting in busts.

7.2 Bank Capital

In the baseline model, banks are assumed to be completely healthy: they are never constrained by their capital abundance. During the Great Recession, however, many banks were capital constrained and indeed, policies were designed to recapitalize them. In this section, I study the effects of these policies and discuss some interesting dynamics.

The standard bank-lending channel (Holmstrom and Tirole, 1997) predicts that credit quantity is constrained when banks have insufficient capital. I capture this effect in a simple, reduced-form manner. In particular, suppose in state b, the rate that banks may issue pooling offers to each borrower is capped at λ, where λ is a rough proxy for the capital abundance of banks. Maintaining the assumption that in state g, pooling offers can be instantaneously available. The analysis in state g is unchanged. In state b, the equilibrium is again characterized by a threshold $\mu_b^*(\lambda)$,[27] as shown in Proposition 4.

Proposition 4. *When $R_t = R_b$, there exists a unique threshold $\mu_b^*(\lambda)$.*

1. *The equilibrium is characterized by a waiting and a pooling region. Borrowers wait if and only if $\mu_t \leq \mu_b^*(\lambda)$.*
2. *$\mu_b^*(\lambda)$ increases strictly with λ.*

Proof. See Appendix A.4, including the closed-form expression for μ_b^*. □

[27]With a slight abuse of notation, $\mu_b^*(\lambda)$ denotes the cutoff for a given λ.

Suppose banks in the economy initially have insufficient capital (low λ), a relevant question is how recapitalization policies–modeled as an increase in λ–affect the recovery process. Conventional wisdom says recovery is accelerated since banks are allowed to issue more credit. Indeed, this is the case when banks are highly undercapitalized, say $\lambda = 0$. However, Proposition 4 implies a countervailing force. In particular, if high types expect such an increase in λ, they prefer to wait a big longer, thus postponing the recovery. In this case, policies designed to inject capital into the banking sector suffer from the renowned Lucas Critique, and the optimal policy needs to balance the relative magnitudes of both effects.

8 Conclusion

Why have some recoveries been slow and others fast, while many others have been accompanied with double dips? How are recovery shapes predicted by the characteristics of the prior economic boom? What role does the financial sector play in the boom-bust-recovery cycle?

This paper makes an attempt to answer the above questions by constructing a model with borrowers who possess private information and banks who can dynamically produce this private information. By introducing the dynamic interactions between borrowers and banks, my paper explains different recoveries. By introducing potential borrowers' decisions to start new businesses, I show how recovery is affected by the size and duration of the prior boom. My paper highlights a channel through which credit standards and fluctuations in borrower quality can affect access to finance. Through this channel, shocks to the aggregate state (TFP for example) can have persistent effects.

The results and mechanisms in my paper can be interpreted more broadly. For instance, recoveries can be from industry-wide distresses, economy-side recessions, and of course financial crises. Borrowers without well-established credit history, such as startups and young businesses, are the best real-world examples for entrepreneurs in my model. These firms were hit harder than larger businesses during the most recent crisis, and have been slower to recover (Mills and McCarthy, 2014). Since these firms account for 50 percent of gross job creation in the U.S. (Decker et al., 2014; Haltiwanger et al., 2013), their weak performance directly contributes to the slow recovery.

Moreover, a majority of these firms have been unable to secure any credit. Banks, who are the most important source of financing (Robb and Robinson, 2012), have been reluctant to extend loans.[28] Banks in my model can be broadly interpreted as any financial institution that is capable of producing information on borrowers and making loans. They can be commercial banks, community banks, venture capitalists, as well as nonbank financial institutions such as credit unions. When banks do not screen, they can also be interpreted as the financial market.

This paper has focused on entrepreneurs who have no well-established credit history with banks. An interesting extension is to allow for relationship borrowing and examine the dynamic implications on recoveries.

[28] Joint Small Business Credit Survey, 2014: https://www.newyorkfed.org/smallbusiness/joint-small-business-credit-survey-2014.html

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Appendix

A Derivations and Proofs

A.1 Proof for Proposition 1

All conditions in the equilibrium definition 1 is easily verified except for borrower optimality. I now verify it is indeed optimal for high type borrowers to accept an immediate pooling offer everywhere. In other words, it is suboptimal to wait at *any* $\mu \in \left[\mu_g^E, \mu_b^E\right]$, given that $d\mu_t = \eta\left(1 - \frac{\mu}{\underline{q}}\right) dt < 0$.

First, condition (11) guarantees that high types never want to wait when $\mu_t = \mu_g^E$.

Second, suppose that high types find it worthwhile to wait at some μ_t. The HJB equation that characterizes the waiting value is:

$$(\rho + \beta s^* + \chi_b) W_g^h = \left(W_g^h\right)' \eta \left(1 - \frac{\mu}{\underline{q}}\right) + \beta s^* \left(R_g - I\right) + \chi_b V_b^h. \tag{18}$$

Take derivative on both sides, it is easily verified that $\left(W_g^h\right)'' < 0$.

Lastly, condition (11) guarantees that $\left(W_g^h\right)' \leq l$ for all $\mu_t \in \left(\mu_g^E, \mu_b^E\right)$, which concludes the proof.

A.2 Extended Proposition 2

In this section, I present the full version of Proposition 2 and provide a proof.

Proposition 5. *When $R_t = R_b$,*

1. *If $\chi_g\left(R_g - R_b\right) + \beta s^*\left(R_b - I\right) \leq (\rho + \beta s^*) c$, there exists a unique $\mu_b^* = \frac{\chi_g\left(R_g - R_b\right) + l(\beta s^* + \eta) + \rho(I + l - R_b)}{l\left(\rho + \beta s^* + \frac{\eta}{\bar{q}}\right)}$:*
   (a) *For $\mu_t \in \left[\mu_g^E, \min\left\{\mu_b^*, \mu_b^E\right\}\right)$, high-type borrowers wait. Only high-type borrowers are financed with screening offers. Investment is delayed. Recovery is slow.*
   (b) *For $\mu_t \in \left(\min\left\{\mu_b^*, \mu_b^E\right\}, \mu_b^E\right]$, all borrowers immediately accept pooling offers $F_p(\mu_t)$. Investment is never delayed. Recovery is fast.*
2. *If $\chi_g\left(R_g - R_b\right) + \beta s^*\left(R_b - I\right) > (\rho + \beta s^*) c$*
   (a) *For $\mu_t \in \left[\mu_g^E, \mu_b^E\right)$, high-type borrowers wait. Only high-type borrowers are financed and with screening offers. Investment is delayed. Recovery is slow.*
   (b) *For $\mu_t = \mu_b^E$, all borrowers immediately accept pooling offers $F_p(\mu_t)$. Pooling offers are issued with a constant rate $p^* = \frac{\rho c}{\left[R_b - F_p(\bar{\mu}_b) - c\right]}$, where $\bar{\mu}_b = \frac{\chi_g\left(R_g - R_b\right) + l\beta s^* + \rho(I + l - R_b)}{l(\rho + \beta s^*)}$. Investment is delayed. Recovery is slow.*

I discuss the two cases in Proposition 2. In fact, $\bar{\mu}_b$ equals μ_b^* if $\eta = 0$. It is the threshold such that high-type borrowers are indifferent between waiting and accepting pooling offers, if they know that the borrower pool will not improve anymore. If $\bar{\mu}_b \leq \mu_b^E$, as in the first case, entry quality is still as high as $\bar{q}$ when μ_t reaches $\bar{\mu}_b$. Thus, a pooling region $\left[\mu_b^*, \mu_b^E\right]$ exists. If $\bar{\mu}_b < \mu_b^E < \mu_b^*$, the pooling region simply shrinks to a single point μ_b^E. The market quality stays at μ_b^E. Potential borrowers with entry cost c are indifferent between entering or not and in equilibrium, a fraction $\frac{1-\mu_b^E}{\mu_b^E}$ of them enter so that the quality stays constant. Pooling offers are made immediately $p^* = \infty$ and are accepted by all borrowers.

If $\bar{\mu}_b > \mu_b^E$, as in the second case, the equilibrium gets more complicated. High-type borrowers will never accept any pooling offer before μ_t reaches $\bar{\mu}_b$. However, an immediate pooling offer at $F_p(\bar{\mu}_b)$ will induce all borrowers to enter the market and thus deteriorate the pool. Thus, any $\mu > \bar{\mu}_b$ cannot be an equilibrium. Meanwhile, any $\mu < \bar{\mu}_b$ cannot be an equilibrium either. High types will never accept a pooling offer at face value $F_p(\mu) > F_p(\bar{\mu}_b)$ and those potential borrowers with cost c will not enter if they cannot receive any offer in state b (Condition (10)). Therefore, the only equilibrium features pooling offers being made at $F_p(\bar{\mu}_b)$ with a delay. The market quality stays at $\bar{\mu}_b$, and pooling offers $F_p(\bar{\mu}_b)$ are made with intensity $p^* = \frac{\rho c}{[R_b - F_p(\bar{\mu}_b) - c]}$. As a result, the continuation value V_b^l equals entry cost c and high types are willing to accept the pooling offers.

Below I provide a simple proof to the first case. The second case can be analyzed similarly.

Proof. I show that it is indeed optimal for high types to stop waiting at μ_b^*. Suppose the high types stop waiting at any arbitrary $\hat{\mu}$. The value function at *any* μ from waiting is:

$$(R_b - I) + (\bar{q} - \mu)\, Const + \frac{\rho I + \chi_g \left(R_g - l(1-\bar{q})\right) - R_b\left(\rho + \chi_g\right)}{\rho + \chi_g + \beta s^*} - \frac{\chi_g l \bar{q}(\bar{q} - \mu)}{\eta + \bar{q}\left(\rho + \chi_g\right) + \bar{q}\beta s^*}. \quad (19)$$

Thus, the boundary conditions $\left(\hat{\mu}, \Psi_b^h(\hat{\mu})\right)$ only matter for $Const$ in the solution. It remains to show that $Const$ is maximized at $\mu_t = \mu_b^*$.

For an arbitrary $\hat{\mu}$,

$$Const = (\bar{q} - \hat{\mu})^{\frac{\bar{q}(\rho + \chi_g + \beta s^*)}{\eta}} \left[-l(1-\hat{\mu}) - \frac{\rho I + \left(R_g - l(1-\bar{q}) - R_b\left(\rho + \chi_g\right)\right)}{\rho + \chi_g + \beta s^*} + \frac{l\bar{q}(\bar{q} - \hat{\mu})\chi_g}{\eta + \bar{q}\left(\rho + \chi_g\right) + \bar{q}\beta s^*} \right]. \quad (20)$$

Straightforward math verifies that $\frac{\partial Const}{\partial \hat{\mu}} = 0$. Moreover,

$$\begin{aligned} sgn\left(\frac{\partial^2 Const}{\partial \hat{\mu}^2}\right)\Big|_{\hat{\mu} = \mu_b^*} &= -sgn\left(\frac{l\eta}{\rho\left[R_b - I - (1-\bar{q})\, l\right] - \chi_g\left(R_g - R_b\right) - \beta s^*(1-\bar{q})\, l}\right) && (21)\\ &< 0. && (22)\end{aligned}$$

where the negative sign comes from the negative denominator, which is guaranteed by the assumption that high types are reluctant to wait at $\mu_t = \bar{q}$:

$$\left(\rho + \beta s^* + \chi_g\right)\left[R_b - I - (1-\bar{q})\, l\right] > \beta s^*(R_b - I) + \chi_g\left[R_g - I - (1-\bar{q})\, l\right]. \quad (23)$$

□

A.3 Proof for Proposition 3

Since bank screening decisions are essentially static, their decisions are easily verified as optimal by Assumption 2. It remains to show that the equilibrium strategies are optimal for high types.

Following the argument in Section A.2 and Assumption 1, the optimality in $\left[\mu_g^E, \mu_b^0\right]$, $\left[\mu_b^0, \mu_b^{dd}\right]$, $\left[\mu_b^s, \mu_b^*\right]$ and $\left[\mu_b^*, \mu_b^E\right]$ directly follows. It remains to verify the optimality when $\mu \in \left[\mu_b^{dd}, \mu_b^s\right]$. In this region, the value of waiting is characterized by

$$\left(\rho + \chi_g\right) W_b^h = \left(W_b^h\right)' \eta \left(1 - \frac{\mu}{\bar{q}}\right) + \chi_g V_g^h \quad (24)$$

with boundary conditions $\left(\mu_b^s, W_b^h\left(\mu_b^s\right)\right)$, where $W_b^h\left(\mu_b^s\right)$ itself is computed as that in Section A.2. Differentiate both sides of Equation (24), it is show that

$$\left(W_b^h\right)'' = \frac{\left(\rho + \chi_g + \frac{\eta}{\bar{q}}\right)\left(W_b^h\right)' - \chi_g l}{\eta\left(1 - \frac{\mu}{\bar{q}}\right)} > 0. \tag{25}$$

Given the optimality at μ_b^s, the convexity of W_b^h on $\left[\mu_b^{dd}, \mu_b^s\right]$, and that μ_b^0 is the unique solution to both value-matching and smooth-pasting conditions when $s_t \equiv 0$, it is verified that it is everywhere optimal to wait when $\mu \in \left[\mu_b^{dd}, \mu_b^s\right]$.

A.4 Proof for Proposition 4

Take χ_g as 0 for simplicity. Everything (including the closed-form solution) goes through with positive χ_g.

The analysis in state g is unchanged. In state b, there exists a threshold $\mu_b^*(\lambda)$ such that high types are willing to accept pooling offers if and only if $\mu \geq \mu_b^*(\lambda)$. The Hamilton-Jacobi-Bellman (HJB) equation in $\left[\underline{q}, \mu_b^*(\lambda)\right]$ is unchanged:

$$\left(\rho + \beta s^*\right) W_b^h = \left(W_b^h\right)' \eta\left(1 - \frac{\mu}{\bar{q}}\right) + \beta s^*\left(R_b - I\right). \tag{26}$$

When banks are constrained, high types continuation value V_b^h at boundary $\mu_b^*(\lambda)$ is different. In particular, it is characterized as:

$$\left(\rho + \beta s^* + \lambda\right) V_b^h = \left(V_b^h\right)' \eta\left(1 - \frac{\mu}{\bar{q}}\right) + \beta s^*\left(R_b - I\right) + \lambda \Psi_b^h(\mu). \tag{27}$$

Recall that $\Psi_b^h(\mu) = R_b - \left[I + (1 - \mu) l\right]$ is the value from accepting an immediate pooling offer. Finally, assume $\frac{\lambda}{\rho+\lambda+\beta s^*}\Psi_b^h(\bar{q}) + \frac{\beta s^*}{\rho+\lambda+\beta s^*}\left(R_b - I\right) < c$ so that high-cost candidates will not enter even if $\mu_t = \bar{q}$. Solving Equation (27) from the right boundary $\left(\bar{q}, \frac{\lambda}{\rho+\lambda+\beta s^*}\Psi_b^h(\bar{q}) + \frac{\beta s^*}{\rho+\lambda+\beta s^*}\left(R_b - I\right)\right)$, and solving Equation (26) with value-matching and smooth-pasting conditions, it is easily derived that

$$\mu_b^*(\lambda) = \frac{l\left\{\eta\left(\rho + \beta s^*\right) + q\left[\left(s^*\right)^2\beta^2 + \eta\lambda + \rho\left(\lambda + \rho\right) + \beta s^*\left(\lambda + 2\rho\right)\right]\right\} - \rho\left(R_b - I\right)\left[\eta + q\left(\beta s^* + \lambda + \rho\right)\right]}{l\left(\beta s^* + \rho + \lambda\right)\left[\eta + q\left(\beta s^* + \rho\right)\right]}. \tag{28}$$

It is easily verified that $\mu_b^*(\lambda)$ strictly increases with λ.

B Detailed Empirical Analysis

In this section, I study in details the determinants of recovery duration and focus on the effect of boom duration, recession depth, and bank screening.

Data Sources

I merge several data sources into three datasets: two samples at the country level and one at the industry level. The first sample includes sequences of real per capita GDP [29] across different countries, collected by the Maddison Project[30] at the annual frequency. These data span from AD 1 to 2010, and cover all countries whose data are available. Bolt and Zanden (2014) explain the underlying methodology on data collection/estimation. For the sake of reliability, I only use the data since 1870. This subsample is weakly balanced[31], containing 165 countries for 141 years. Other control variables include measures of bank capital and bank loans from Schularick and Taylor (2012), and measure of domestic private debt from IMF and the World Bank[32].

The second sample covers quarterly real GDP for OECD countries[33] from 1960 to 2015, including 25 countries for 223 quarters. This sample serves two functions. First, it uses real GDP to identify different phases of the business cycle, and is thus a robust check. Second, it deploys quarterly-level data, which capture business cycles that occur at higher frequency.

The third sample combines two different datasets. The first dataset covers industry-level gross GDP from the Bureau of Economic Analysis (BEA)[34], containing 58 U.S. industries from 1947 to 2014 [35]. The second dataset are obtained from the Annual Statement Studies published by the Risk Management Association (RMA). These studies provide the number of different types of financial reports that banks collect from borrowers in different industries. Financial reports are further classified into five mutually exclusive categories–unqualified audit, review, compilation, tax return, and other. These categories have different qualities, with unqualified audits being of the highest quality and tax returns the lowest. **?** provide a detailed introduction to the data set, as well as issues regarding sample representativeness. Besides the numbers on financial reports, the RMA Annual Statement Studies also report the value of total sales from these borrowers, which can be used to proxy industry performance. By merging these two datasets, I generate a sample with output and bank screening measured for each industry.

Algorithm to Identify Peaks, Troughs, and Recoveries

This section describes the algorithm to identify peaks, troughs, and recoveries, given the time series $\{\tilde{y}_t\}_{t=1}^{T}$. These series can be the detrended real GDP per capita of a country, the detrended real GDP of an OECD country, or the detrended general output of a U.S. industry.

1. Initialization: $c = 0$, $\tilde{y}_c^{Pk} = 0$, $\left(t_c^{Pk}, t_c^{Tr}, t_c^{Rcy}\right) = (0, 0, 0)$, and $\left(I_c^{Pk}, I_c^{Tr}, I_c^{Rcy}\right) = (0, 0, 0)$;

2. For $t = 2 : (T - 1)$

   (a) If $\tilde{y}_t > \max\left\{\tilde{y}_{t-1}, \tilde{y}_{t+1}, \tilde{y}_c^{Pk}\right\}$, then $\tilde{y}_c^{Pk} = \tilde{y}_t$ and $t_c^{Pk} = t$;

   (b) If $\tilde{y}_t < 0$ and $\tilde{y}_t < \min\{\tilde{y}_{t-1}, \tilde{y}_{t+1}\}$, then $c = c + 1$, $\tilde{y}_c^{Tr} = \tilde{y}_t$, $t_c^{Tr} = t$, $I_c^{Pk} = 1$, and $I_c^{Tr} = 1$;

   (c) If $\tilde{y}_{t-1} < 0$ and $\tilde{y}_t > 0$, then $\tilde{y}_c^{Rcy} = \tilde{y}_t$, then $\tilde{y}_c^{Tr} = \tilde{y}_t$, $t_c^{Tr} = t$, and $I_c^{Rcy} = 1$;

   (d) Re-initialization: $\tilde{y}_c^{Pk} = 0$, $\left(t_c^{Pk}, t_c^{Tr}, t_c^{Rcy}\right) = (0, 0, 0)$, and $\left(I_c^{Pk}, I_c^{Tr}, I_c^{Rcy}\right) = (0, 0, 0)$. Return to step (a).

[29] According to Reinhart and Rogoff (2014), real GDP per capita is a good approximation for living standards.

[30] The Maddison-Project, http://www.ggdc.net/maddison/maddison-project/home.htm, 2013 version.

[31] The very few missing observations are filled by linear interpolation.

[32] http://data.worldbank.org/indicator/FS.AST.PRVT.GD.ZS

[33] https://stats.oecd.org/.

[34] http://www.bea.gov/industry/

[35] The original data contain 71 three-digit industries. However, GDP data for certain industries are not available. Therefore, I combine them into two-digit level industries, and the sample size gets reduced.

Variable Definition

Peak, Trough and Recovery With a slight abuse of notation, let $\{y_t\}$ denote the sequences of both *nature log* of real GDP and real GDP per capita. For each country/industry, I detrend $\{y_t\}$ using the band-pass filter[36] (Christiano and Fitzgerald, 2003) and extract the components between two and eight years. For quarterly-level data, I extract the components between six and 32 quarters. The detrended sequences $\{\tilde{y}_t\}$ capture the business-cycle frequency components in output, which are then used to identify peaks, troughs, and recoveries. For each country/industry, I define a cycle as the period between two subsequent peaks in $\{\tilde{y}_t\}$. The definition for peaks is standard in the literature: all years/quarters that $\{\tilde{y}_t\}$ attain local maxima with minor exceptions. The exceptions basically allow for double dips and guarantee $\tilde{y}_t$ to be negative in the trough year/quarter that locates between two peaks. Troughs are defined as the first year/quarter after a peak that $\{\tilde{y}_t\}$ attain a local minimum that is negative. Recession size is defined as $\tilde{y}_t$ in the peak year/quarter relative to $\tilde{y}_t$ in the trough year/quarter. Finally, recovery is identified as the first year/quarter that $\{\tilde{y}_t\}$ rise above zero. The formal definitions are available in Table 1, and Appendix B provides an algorithm for implementation. Figure 12 illustrates the above definitions graphically. It contains two cycles, and the second one experiences a double dip.

[Table 1 and Figure 12 about here.]

Bank Screening I use data from the RMA to measure bank screening. In particular, I approximate bank screening by the fraction of financial reports collected by their banks that are of high quality (Unqualified Audit in this case). That is,

$$SCR_{it} = \frac{\text{No. of Unqualified Audits Collcted}}{\text{No. of All Reports Collected}}.$$

Summary Statistics

Table 2 summarizes samples from all data sources. The top, middle, and bottom panel respectively describe data from the Maddison Project, OECD, and U.S. industries. An average country in the Maddison sample has about 31.4 cycles,[37] and an average cycle lasts for 6.1 years. The duration of each recovery is right-skewed: while over 50% of the recoveries take less than two years, the longest one lasts up to 6 years. While an average boom lasts about 1.0 years, the maximal boom persists for 4 years. During recoveries, about 8% experience double dips. This number is significantly smaller than the one reported by Reinhart and Rogoff (2014) (43%), which focuses on recoveries after banking crises.[38]

[Table 2 about here.]

Cycles in the OECD sample are much shorter: an average cycle lasts 16.1 quarters. By exploiting quarterly-level data, I am able to capture more cycles at higher frequency. For the same reason, double-dips are much more frequent during recoveries (20%). Summary statistics of an average industry in the U.S. are mostly consistent with an average country.

The top two panels of Figure 13 plot the distribution of recovery duration and boom duration. The bottom panels imply that both recession depth and the duration of the preceding boom are positively correlated with the recovery duration. Figure 14 and 15 in the Appendix show the same patterns hold in the OECD and industry sample. Next, I examine these correlations in more details by controlling for more variables.

[36]The program is available at https://www.frbatlanta.org/cqer/research/bpf.aspx. The results are also robust to Hodrick-Prescott filter and Baxter-King filter.

[37]The first two cycles are dropped to make the filtered sequences stable.

[38]The definition for double-dip is slightly different. Reinhart and Rogoff (2014) did not detrend the data but instead defined double dip as "at least one renewed downturn (decline) before the previous peak was matched or surpassed".

Empirical Specification

For country-level studies, Equation (29) is used as the main specification:

$$T_{i,c}^{Rcy} = \alpha + \beta_1 T_{i,c}^{Bm} + \beta_2 T_{i,c}^{Rcn} + \beta_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \iota \cdot \mathbf{x} + \gamma_i + \varepsilon_{it}, \tag{29}$$

where $T_{i,c}^{Rcy}$ measures the number of years (quarters) that country i takes to recover in the $c'th$ cycle. $T_{i,c}^{Bm}$ and $T_{i,c}^{Rcn}$ respectively represent boom and recession duration. $\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}$ is the size of recession, with the latter measured by the drop in $\tilde{y}_t$ in the trough year relative to the peak year. $\mathbf{x}$ is a vector of other covariates, including changes in $\frac{\text{Private Debt}}{\text{GDP}}$, $\frac{\text{Bank Capital}}{\text{GDP}}$, and $\frac{\text{Bank Loans}}{\text{GDP}}$. Country fixed effects are included as γ_i. The theoretical model predicts that the coefficients β_1 and β_2 are positive and significantly different from zero.

A similar specification is used to study the determinants of double dip recessions.

$$N_{i,c}^{Dip} = a + b_1 T_{i,c}^{Bm} + b_2 T_{i,c}^{Rcn} + b_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \gamma_i + u_{it}, \tag{30}$$

where $N_{i,c}^{Dip}$ counts the number of dips during the recovery of country i in cycle c. Again, the theoretical model predicts that the coefficients b_1 and b_2 are positive and significantly different from zero.

$$T_{i,c}^{Rcy} = \delta_0 + \delta_1 SCR_{ic}^{Rcn} + \delta_2 SCR_{ic}^{Pk} + \delta_3 T_{i,c}^{Bm} + \delta_4 T_{i,c}^{Rcn} + \delta_5 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Rcn}\right) + v_{it}, \tag{31}$$

where SCR_{ic}^{Rcn} and SCR_{ic}^{Pk} respectively measures bank screening in the recession and peak year. The theoretical model predicts δ_1 to be positive and δ_2 to be negative. $T_{i,c}^{Rcy}$ measures the number of years (quarters) that country i takes to recover in the $c'th$ cycle. $T_{i,c}^{Bm}$ and $T_{i,c}^{Rcn}$ respectively represent boom and recession duration. $\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}$ is the size of recession, with the latter measured by the drop in $\tilde{y}_t$ in the trough year relative to the peak year. The theoretical model predicts that δ_1, δ_3, and δ_5 are positive and significant.

Estimation Results

Table 4 reports the results of specification (29) using the Maddison data. All standard errors are clustered at the country level. Column (1) to (5) show that one additional year spent in a boom is likely to postpone the following recovery by some period between 0.173 and 0.259 years. While the average recovery takes 2.2 years, this accounts for a delay between 7.9% and 11.8%. Meanwhile, one more standard deviation in recession size (0.2) delays the recovery by a length between 0.08 and 0.18 years. These coefficients are significant both statistically and economically. Moreover, the results are robust to the control of country fixed effects and continue to hold in two subsamples: the first one only includes developed countries over the entire period; the second one only uses years post the World War II. Column (5) separates peak size from trough size, and show that the result is mainly driven by the peak size.

Table 5 reports the effects of private debt, bank asset and bank loans on recovery duration. All three variables are scaled by the level of GDP. The total numbers of observations shrink dramatically due to data availability. Column (1) shows that the result still holds after changes in Debt/GDP are taken into consideration. Column (2) shows drop in bank loan over GDP from the boom year to the recession year is positively correlated with recovery duration. In addition, I have also controlled for a dummy that indicates whether the recession is a crisis episode identified by Reinhart and Rogoff (2008). The coefficient (not shown) is positive but insignificant.

[Table 4, 5, 6, 7, and 8 about here.]

Table 6 reports the results on the determinants of double-dips. Results show that one more year in boom increases the average number of dips between 0.025 and 0.154. One more standard deviation in recession size also increases the number of dips by 0.13 and 0.92. These results are not robust to the filter that I use. In particular, all coefficients become insignificant when I use two-sided filters (band-pass and Baxter-King), which also remove components that occur at high frequency (< 2years).

The results on OECD countries are reported in Table 7; the results on U.S. industries are reported in Table 8. These results confirm the previous findings using the Maddison data. Overall, longer booms and larger recessions are correlated with slower recoveries.

Table 10 reports the results of running specification (31). One percentage increase in screening effort in the recession postpones the subsequent recovery by some period between 0.04 and 0.063 years. Meanwhile, one percentage increase in screening effort in the boom year decreases the recovery duration by 0.022 years.

Tables

Table 1 Variable Definition for Empirical Analysis

Variable	Definition
Peak	All years/quarter that $\{\tilde{y}_t\}$ attain local maxima, excluding 1) those below zero ($\tilde{y}_t < 0$); 2) those $\{\tilde{y}_t\}$ have never fallen below zero between this local maximum and the previous local maximum. Formally, the peak of the c'th cycle, t_c^{Pk} satisfies following conditions: 1. $\tilde{y}_{t_c^{Pk}} > \max\left\{\tilde{y}_{t_c^{Pk}-1}, \tilde{y}_{t_c^{Pk}+1}\right\}$; 2. $\tilde{y}_{t_c^{Pk}} > 0$; 3. $\exists\tau \in \left(t_{c-1}^{Pk}, t_c^{Pk}\right)\ s.t.\ \tilde{y}_\tau < 0$ 4. $\nexists\tau \in \left(t_c^{Pk}, t_{c+1}^{Pk}\right)\ s.t. \tilde{y}_\tau > \tilde{y}_{t_c^{Pk}}$.
Trough	The first year/quarter that $\{\tilde{y}_t\}$ attain local minima after a peak, excluding those above zero. Formally, the trough year of the c'th cycle, t_c^{Tr} satisfies following conditions: 1. $\tilde{y}_{t_c^{Tr}} < \min\left\{\tilde{y}_{t_c^{Tr}-1}, \tilde{y}_{t_c^{Tr}+1}\right\}$; 2. $\tilde{y}_{t_c^{Tr}} < 0$; 3. $\nexists\tau \in \left(t_c^{Pk}, t_c^{Tr}\right)\ s.t.\ \tilde{y}_\tau$ satisfies both 1 and 2.
Recovery	The first year/quarter that $\{\tilde{y}_t\}$ resume zero , excluding those with subsequent falling before the next peak. Formally, the recovery year of the c'th cycle, t_c^{Rcy} satisfies following conditions: 1. $\tilde{y}_{t_c^{Rcy}} > 0,\ \tilde{y}_{t_c^{Rcy}-1} < 0$;
Dip	The year/quarter that $\{\tilde{y}_t\}$ attain a local maxima before peak. Formally, a dip year t_c^{Dip} satisfies 1. $\tilde{y}_{t_c^{Dip}} < \tilde{y}_{t_c^{Pk}}$; 2. $\tilde{y}_{t_c^{Dip}} > \max\left\{\tilde{y}_{t_c^{Dip}-1}, \tilde{y}_{t_c^{Dip}+1}\right\}$.
Boom duration	The number of years/quarters between recovery and peak, $T_{i,c}^{Bm} = t_{i,c}^{Pk} - t_{i,c-1}^{Rcy}$.
Recovery duration	The number of years/quarters between trough and duration, $T_{i,c}^{Rcy} = t_{i,c}^{Rcy} - t_{i,c}^{Tr}$.
Recessions size	$\tilde{y}_t$ in the peak year relative to $\tilde{y}_t$ in the trough year, $\tilde{y}_{t_{i,c}^{Pk}} - \tilde{y}_{t_{i,c}^{Tr}}$.

Table 2 Summary Statistics

This table presents summary statistics for the Maddison data (top panel), OECD data (middle panel), and U.S. industry data (bottom panel).

	N	Mean	Max	Min	SD	10^{th}	50^{th}	90^{th}
Country	165							
Number of Cycles per Country		31.4	39	24	3.5	27	32	34
Recovery Duration (year)		2.2	6	1	1.0	1	2	3
Boom Duration (year)		1.0	4	0	0.9	0	1	2
Recession Duration (year)		2.9	7	1	1.3	1	3	5
Recession Size		0.2	1	0	0.2	0	0	0
Average Cycle Length (year)		6.1	12	2	2.3	3	7	9
Number of Dips per Cycle		1.1	3	0	0.4	1	1	2

	N	Mean	Max	Min	SD	10^{th}	50^{th}	90^{th}
country	25							
Number of Cycles per Country		15.0	20	11	2.0	13	15	19
Recovery Duration (quarter)		5.4	15	1	3.3	2	5	10
Boom Duration (quarter)		3.9	19	0	2.9	1	3	8
recession_time		7.0	18	1	3.4	4	6	12
Recession Size		0.0	0	0	0.0	0	0	0
Average Cycle Length (quarter)		16.1	43	6	6.6	8	15	25
Number of Dips per Cycle		1.2	3	0	0.5	1	1	2

	N	Mean	Max	Min	SD	10^{th}	50^{th}	90^{th}
Industry	56							
Number of Cycles per Industry		14.5	18	12	1.7	12	14	16
Recovery Duration		2.0	5	1	0.9	1	2	3
Boom Duration (year)		0.9	4	0	0.9	0	1	2
Recession Size		0.2	1	0	0.2	0	0	0
Average Cycle Length (year)		5.4	10	2	2.1	3	5	8
Number of Dips per Cycle		1.1	2	1	0.3	1	1	1

Table 3 Summary Statistics

This table presents summary statistics for the RMA data.

	Mean	Max	Min	SD	10^{th}	50^{th}	90^{th}
Number of Statements	1448	21898	21	2249.4	118	722	3410
Unqualified	262	2705	2	374.3	25	123	658
Revenue	248	3313	1	439.2	13	119	564
Compilation	271	3011	0	403.4	16	139	688
Tax Report	221	11902	0	705.1	0	45	476
Unqualified/Total	0.23	0.72	0.02	0.14	0.08	0.20	0.41

Table 4 The Determinant of Recovery Duration – Maddison Data

This table presents coefficients from regressions

$$T_{i,c}^{Rcy} = \alpha + \beta_1 T_{i,c}^{Bm} + \beta_2 T_{i,c}^{Rcn} + \beta_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \iota \cdot \mathbf{x} + \gamma_i + \varepsilon_{it}.$$

using data from the Maddison project. Standard errors are clustered at the country level.

	(1) Full Sample	(2) Full Sample	(3) Developed Countries	(4) Post World War II	(5) Full Sample
Boom Duration (year)	0.259***	0.173***	0.205***	0.178***	0.174***
	(0.028)	(0.032)	(0.040)	(0.036)	(0.031)
Recession Duration (year)	0.069***	-0.007	0.029	-0.051*	-0.026
	(0.017)	(0.026)	(0.032)	(0.026)	(0.025)
Recession Size	0.924***	0.439***	0.879*	0.408**	
	(0.125)	(0.152)	(0.492)	(0.183)	
Peak Size					6.556***
					(0.735)
Trough Size					-3.088***
					(0.416)
Constant	1.560***	2.232***	1.634***	2.420***	1.937***
	(0.065)	(0.147)	(0.082)	(0.386)	(0.142)
Specification	OLS	Fixed-Effects	Fixed-Effects	Fixed-Effects	Fixed-Effects
Country Dummy#	No	Yes	Yes	Yes	Yes
N	1563	1563	902	1105	1563
R^2	0.129	0.260	0.193	0.283	0.301

***,**,*: Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

Table 5 More Tests on Recovery Duration – Maddison Data

This table presents coefficients from regressions

$$T_{i,c}^{Rcy} = \alpha + \beta_1 T_{i,c}^{Bm} + \beta_2 T_{i,c}^{Rcn} + \beta_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \iota \cdot \mathbf{x} + \gamma_i + \varepsilon_{it}.$$

using data from the Maddison project. Standard errors are clustered at the country level.

	(1)	(2)
Boom Duration (year)	0.097	0.176*
	(0.061)	(0.086)
Recession Duration (year)	0.053	0.079
	(0.051)	(0.050)
Recession Size	12.561***	0.794
	(3.196)	(1.352)
Rise in Debt/GDP	-0.005	
	(0.015)	
Drop in Debt/GDP	-0.008	
	(0.008)	
Drop in bank loans/GDP		0.001*
		(0.001)
Rise in bank loans/GDP		-0.000
		(0.000)
Constant	0.763***	1.606***
	(0.122)	(0.143)
Specification	Fixed-Effects	Fixed-Effects
Country Dummy#	Yes	Yes
N	666	271
R^2	0.251	0.109

***,**,*: Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

Table 6 The Determinant of Double Dip – Maddison Data

This table presents coefficients/marginal probabilities from regressions

$$N_{i,c}^{Dip} = a + b_1 T_{i,c}^{Bm} + b_2 T_{i,c}^{Rcn} + b_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr} \right) + \gamma_i + u_{it}.$$

using data from the Maddison project. The dependent variable counts the number of dips occurred during the recovery. Standard errors are clustered at the country level.

	(1)	(2)
Boom Duration (year)	0.154***	0.025**
	(0.039)	(0.013)
Recession Size	4.600***	0.662*
	(1.085)	(0.372)
Peak Size		
Trough Size		
Specification	OLS	Fixed-Effects
Country Dummy#	No	Yes
N	1536	1636
R^2	0.054	0.123

***,**,* Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

Table 7 Regression Results using OECD Data

This table presents coefficients from regressions

$$T_{i,c}^{Rcy} = \alpha + \beta_1 T_{i,c}^{Bm} + \beta_2 T_{i,c}^{Rcn} + \beta_3 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \iota \cdot \mathbf{x} + \gamma_i + \varepsilon_{it}.$$

using data from the OECD database. Standard errors are clustered at the country level.

	(1)	(2)	(3)
Boom Duration (quarter)	0.168**	0.150*	0.151*
	(0.072)	(0.086)	(0.086)
Recession Duration (quarter)	0.274***	0.248***	0.243***
	(0.066)	(0.080)	(0.079)
Recession Size	22.977***	26.879***	
	(5.156)	(8.756)	
Peak Size			53.404**
			(19.870)
Trough Size			5.497
			(21.369)
Constant	2.099***	1.942**	1.921**
	(0.500)	(0.723)	(0.699)
Specification	OLS	Fixed-Effects	Fixed-Effects
Country Dummy#	No	Yes	Yes
N	273	273	273
R^2	0.166	0.242	0.249

***,**,*: Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

Table 8 Regression Results using US 3-digit Industry Data

This table presents coefficients from regressions

$$T^{Rcy}_{i,c} = \alpha + \beta_1 T^{Bm}_{i,c} + \beta_2 T^{Rcn}_{i,c} + \beta_3 \left(\tilde{y}^{Pk}_{i,c} - \tilde{y}^{Tr}_{i,c}\right) + \iota \cdot \mathbf{x} + \gamma_i + \varepsilon_{it}.$$

using data from U.S. three-digit industries. Standard errors are clustered at the industry level.

	(1) Full Sample	(2) Full Sample	(3) Balanced Sample
Boom Duration (year)	0.164***	0.139**	0.164***
	(0.060)	(0.063)	(0.059)
Recession Duration (year)	0.038	-0.019	-0.033
	(0.031)	(0.042)	(0.042)
Recession Size	1.319***	1.112*	
	(0.344)	(0.649)	
Peak Size			5.543***
			(1.378)
Trough Size			-3.028***
			(1.109)
Constant	1.580***	1.778***	1.785***
	(0.105)	(0.089)	(0.083)
Specification	OLS	Fixed-Effects	Fixed-Effects
naics3 Dummy#	No	Yes	Yes
N	439	439	439
R^2	0.076	0.203	0.235

***,**,*: Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

Table 9 Average Screening over the Business Cycle

This table compares the average screening across different stages of the business cycle. Screening is measured by fraction of financial statements that are unqualified audits–as the dependent variable. A linear trend is removed from the original sequence.

	Mean	Max	Min
Recession	0.005	0.486	-0.205
Recovery	0.006	0.486	-0.232
Boom	-0.003	0.480	-0.230

Table 10 Bank Screening and Recovery Duration

	(1)	(2)
Screening in Recession Year (%)	0.040*	0.063**
	(0.024)	(0.028)
Screening in Boom Year (%)		-0.022
		(0.029)
Boom Duration (year)	0.200**	0.177**
	(0.082)	(0.083)
Recession Duration (year)	-0.036	-0.012
	(0.072)	(0.069)
Recession Size	-0.189	-0.240
	(1.092)	(1.160)
Constant	2.481***	2.437***
	(0.257)	(0.306)
Specification	Fixed-Effects	Fixed-Effects
naics_3 Dummy#	Yes	Yes
N	185	173
R^2	0.436	0.480

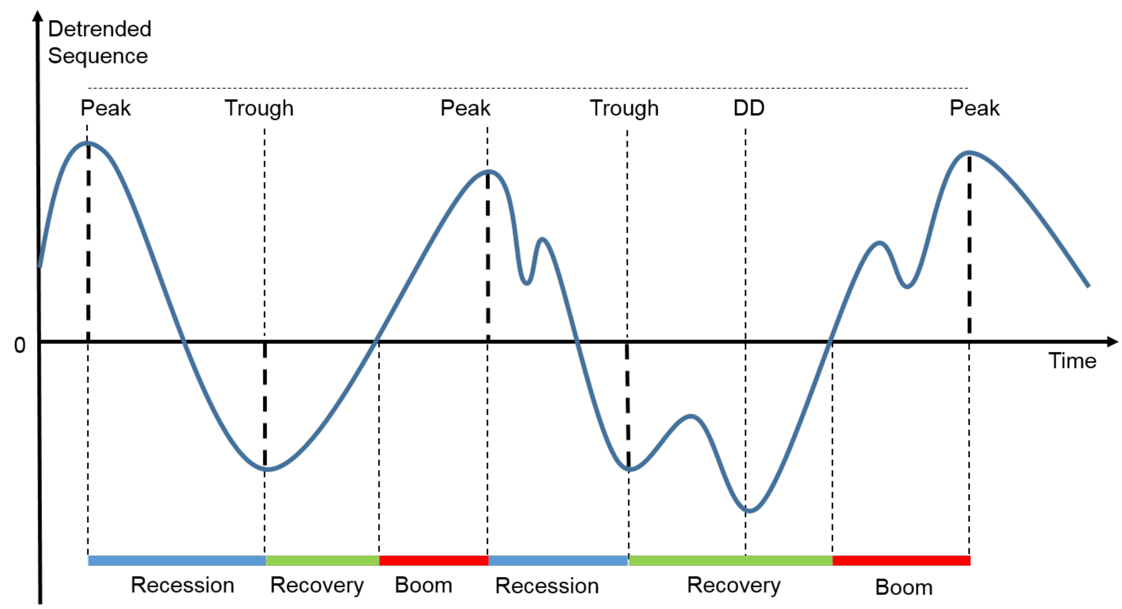
This table presents coefficients from regressions

$$T_{i,c}^{Rcy} = \alpha + \beta_0 \times SCR_{i,c}^{Rcn} + \beta_1 SCR_{i,c}^{Pk} + \beta_1 T_{i,c}^{Bm} + \beta_2 \left(\tilde{y}_{i,c}^{Pk} - \tilde{y}_{i,c}^{Tr}\right) + \gamma_i + \varepsilon_{it}.$$

using data from U.S. three-digit industries. Standard errors are clustered at the industry level. ***,**,*: Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively.

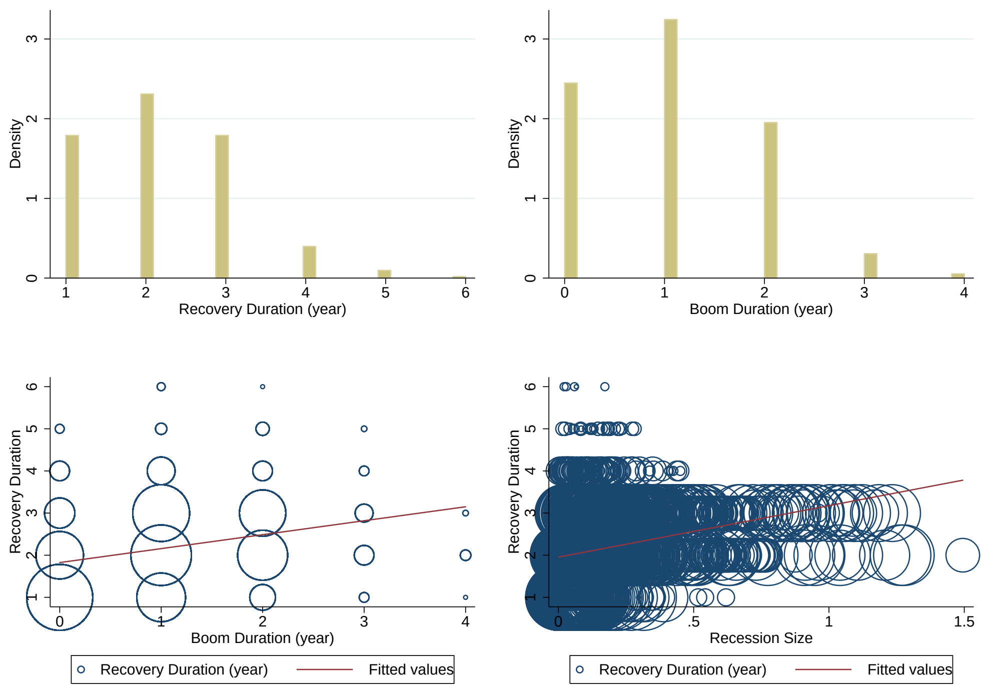
Figures

Figure 12 Business Cycle Illustration



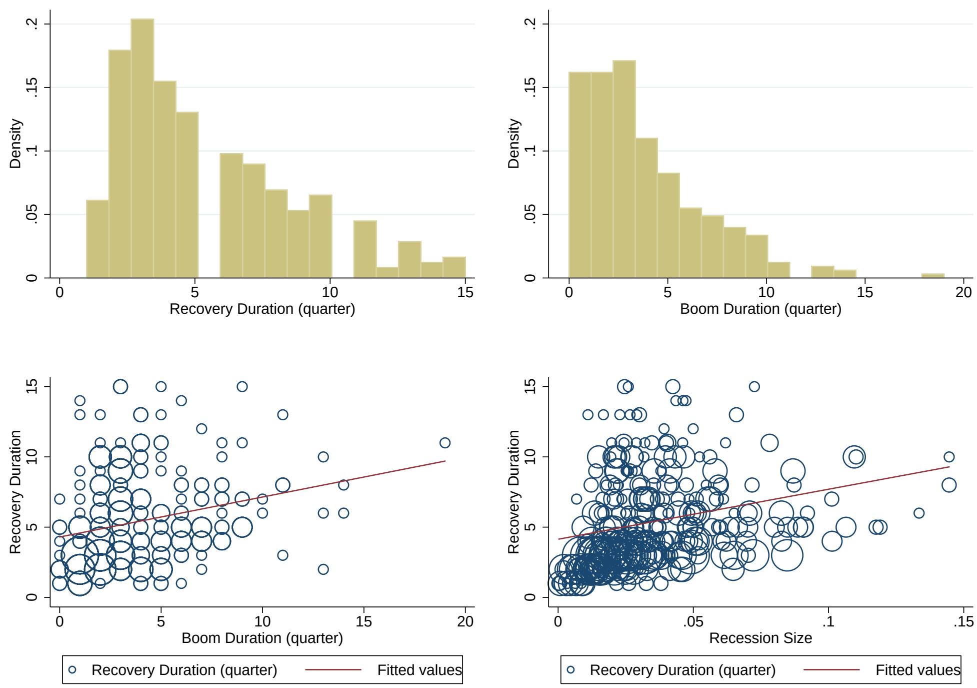
This figure illustrates a typical identification of the different stage of a business cycle. DD is the abbreviation for double dips.

Figure 13 Boom Duration, Recession Size, and Recovery Duration in the Maddison Data



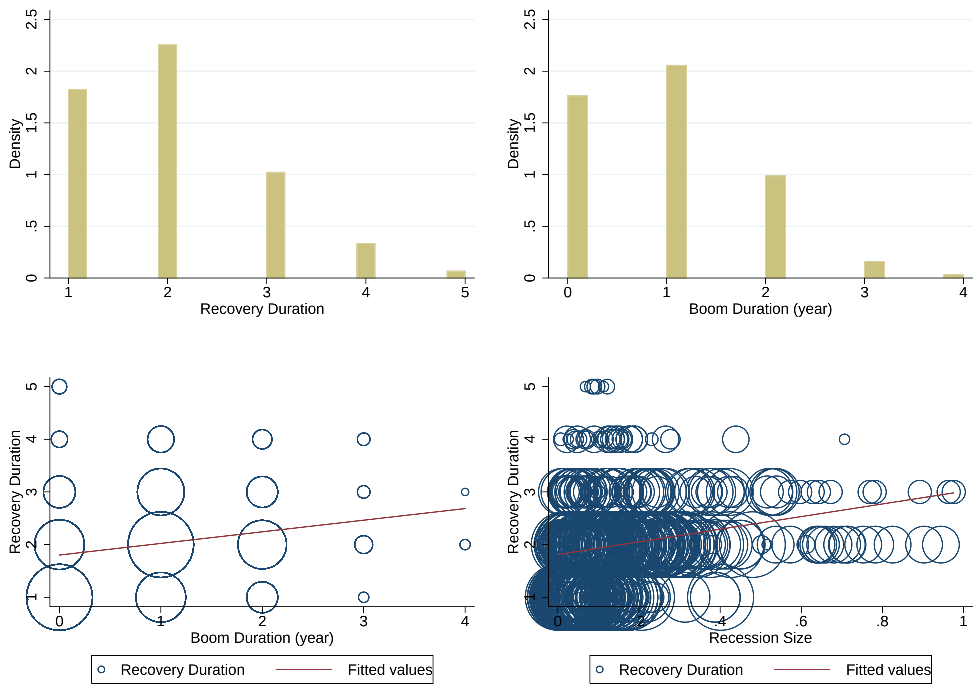
This figure shows the distribution of recovery duration, boom duration, and the correlation between these two, as well as the correlation between recovery duration and recession size. The data are obtained from the Maddison project on world-wide real GDP per capital.

Figure 14 Boom Duration, Recession Size, and Recovery Duration in the OECD Data



This figure shows the distribution of recovery duration, boom duration, and the correlation between these two, as well as the correlation between recovery duration and recession size. The data are obtained from all OECD countries on real GDP.

Figure 15 Boom Duration, Recession Size, and Recovery Duration in the US Industry Data



This figure shows the distribution of recovery duration, boom duration, and the correlation between these two, as well as the correlation between recovery duration and recession size. The data are obtained from industries in the U.S.