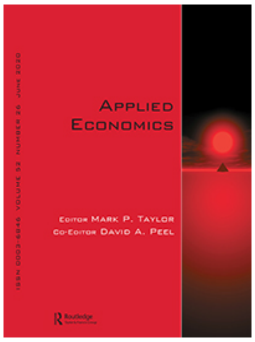


Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Making economics more useful: how technological eclecticism could help

Amar Bhidé

To cite this article: Amar Bhidé (2020) Making economics more useful: how technological eclecticism could help, Applied Economics, 52:26, 2862-2881, DOI: 10.1080/00036846.2019.1696939

To link to this article: https://doi.org/10.1080/00036846.2019.1696939

APPLIED ECONOMICS
2020, VOL. 52, NO. 26, 2862–2881
https://doi.org/10.1080/00036846.2019.1696939

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Making economics more useful: how technological eclecticism could help

Amar Bhidé

Tufts University (and visiting Harvard University AY 2020-21), MA, USA

ABSTRACT
Keynes thought it would be 'splendid' if economists became more like dentists. Disciplinary economics has instead become more like physics in focusing on concise, universal propositions verified through decisive tests. This focus, I argue, limits the practical utility of the discipline because universal propositions form only a part of new policy recipes. I further suggest that, as in engineering and medicine, developing economic recipes requires eclectic combinations of suggestive tests and judgement. Additionally, I offer a detailed example of how a simulation model can help evaluate new policy combinations that affect the screening of loan applications.

KEYWORDS
Economic methodology; simulations; banking; regulation; judgement

JEL CLASSIFICATION
B40; G21

> "Modern engineers are seen as taking over their knowledge from scientists and, by some occasionally dramatic but probably intellectually uninteresting process, using this knowledge to fashion material artefacts … Engineers know from experience that this view is untrue … my career as a research engineer and teacher has been spent producing and organizing knowledge that scientists for the most part do not address."
>
> Walter Vincenti (1990): *What Engineers Know*

Economists who favour policies derived from scientific propositions often say little about how this might be accomplished. Milton Friedman's influential 1953 essay for instance asserts that 'positive' economics – the scientific side – must precede any 'normative' policy prescriptions. Whatever our goals, he argues, we cannot make sensible policy choices if we can't reliably predict their consequences. Furthermore, after asserting the priority of scientific economic propositions, Friedman devotes the rest of the essay to their nature and verification, saying nothing about how scientific propositions map into specific policies or how we might evaluate the effectiveness of these policies.

But in engineering and medicine, scientific understanding does not always come first. Important advances from steam engines to vaccinations, have preceded knowledge of the underlying laws of nature.[1] And even when science leads, as in the development of transistor radios and MRIs, useful technologies do not mechanically follow. Scientific 'propositions' and technological 'prescriptions,' to use Mokyr's (2002) categories, have distinctive features. As Vincenti (1990, 4) argues, 'technology, though it may apply science, is not the same as or entirely applied science.' Crucially, technology is almost invariably more complex than the science it might incorporate, and the development of technological knowledge reflects this complexity: Developers eclectically combine many techniques to test the performance of alternative designs. Moreover, test results are typically suggestive rather than decisive, complementing but not replacing judgements and hunches (Table 1).

My paper argues that good economic practice also requires complex recipes selected through eclectic combinations of tests and judgement. And, to 'show' and not just 'tell,' I provide an illustrative example of using simulations to evaluate and legitimize regulatory choices that affect the extension of credit.

Prior work on the connection of economics and technology includes Dulman (1989) on how railroad engineers developed Discounted Cash Flow (DCF)

CONTACT Amar Bhidé amar@bhide.net

Samuel Markson provided invaluable tutoring in Mathematica and considerable specific help in writing the code used for this paper. I am also grateful for reactions and suggestions from an anonymous referee, Martin Blåvarg, Bo Becker, Raicho Bojilov, Caitlin Bowler, Adam Brandenburger, Charles Calomiris, Nancy Cartwright, David Chaffetz, Srikant Datar, Mark Flood, Richard Frankel, Benjamin Friedman, Iftekhar Hasan, David Hendry, Bill Janeway, John Kay, Mervyn King, Arnold Kling, John McArthur, Richard Nelson, Michael Roberts, Vernon Smith, Andrei Shleifer, Judy Stephenson, Howard Stevenson, Harborne Stuart, Mark Taylor (the editor), Ernst-Ludwig von Thadden, Lawrence Weiss, Sidney Winter, Stefano Zedda and Gylfi Zoega.

[1]Recounting Henderson's quip that 'until 1850, the steam engine did more for science than science did for the steam engine,' physicist Malcolm Longair (2003, 223) writes that James Watt's 1765 invention of a condenser, made in the course of repairing a steam engine, 'led to the underpinning of the whole of thermodynamics.'

Table 1. Differences in idealized knowledge and tests.

Nature of:	Science	Technology
Knowledge	Universal, concisely specified propositions	Complex recipes designed for specific circumstances and purposes
Tests	Objective and decisive (as per community consensus)	Eclectic combinations producing suggestive results

techniques and engineering academics working on capital investment problems created the field of engineering economics; Roth's (2002) 'The Economist as Engineer' on market design; Cherrier and Saidi's (2019) history of collaborations between engineers and economists at Stanford; and Kay and King (forthcoming) on applying the practical problem solving approach of engineers to economics.

My interest in the technology-economics connection is part of a broader, ongoing study of the nature and development of knowledge in practical fields such as engineering, medicine and business. That broader study examines several activities and tasks undertaken, such as goal setting, conjecture, testing and evaluation, codification, and communication; the multifarious techniques used; and, the risks of rigid adherence to scientific methodologies (Bhidé 2019a). Here I focus more narrowly on testing and evaluation and on the use of simulations.

Outline. The main sections of this paper:

(1) Examine differences between science and technology (outlined in Table 1).
(2) Argue that the scientific goals and methods of disciplinary economics constrain its practical utility in evaluating new policy combinations.
(3) Show how simulations can ease these constraints by facilitating reasoned collaborative judgements.
(4) Provide an illustrative example of a simulation model designed to evaluate the joint effects of policies that affect credit extension.
(5) Describe the outputs of the simulation and their practical policy implications.
(6) Offer concluding comments.

I. Differences in science and technology

Scientific knowledge and tests

Scientific communities favour concise, universal propositions (such as Newton's second law of motion, $F = ma$, and Einstein's law of mass-energy equivalence, $E = mc^2$) whose truth values they can objectively verify to each other's satisfaction.[2] Sometimes, observations of natural outcomes, such as planetary orbits, provide an adequate basis for satisfactory verification. Often however, verifying general propositions requires an artificially constructed apparatus. Galileo's falling body experiments sought to unnaturally isolate the effect of gravity from other forces such as friction (Cartwright 2007, 223). Similarly, Boyle's celebrated 17th century pump 'ma[d]e accessible and manifest the invisible, and normally insensible, effects of the air. (Shapin 1996, 98).' And, unlike the scientific propositions themselves, the experimental apparatuses can be highly elaborate. Boyle's air pump, constructed with the assistance of Robert Hooke was, for its time, an engineering feat.

Using an artificial apparatus – and often indirect proxies for the variables of interest – requires scientific communities to agree on what evidence supports or warrants the rejection of a proposition. Even the acceptance of observations of natural phenomena requires a consensus. Galileo's sceptical contemporaries had no compelling reason to trust that the moons of Jupiter he tried to show them through his telescope really existed (Shapin 1996, 72).

Complexity of technical recipes

Technologies – 'technical recipes' in Baldwin's (2018) evocative metaphor – cannot be reduced to concisely codified, universal propositions. Requiring surgeons to wash their hands is a striking exception; and, even hand washing is just one step in a surgical procedure. Typically, several factors make useful technical recipes and their development complex.

Technical recipes must solve myriad technical problems. For instance, Sir George Cayley enun-

[2]Although scientific fields can vary considerably (Nelson 2016), science advances with 'general statements of steadily increasing explanatory power' according to zoologist Peter Medawar (1982, 29), that 'annihilate' the need to know particular facts. 'Biology before Darwin was almost all facts,' writes Medawar but now is 'over the hump.' Generality also seems to affect status. August Comte, considered the first modern philosopher of science, arranged the sciences "in the order of generality of the principles they establish[ed] (Knight 1921, 8). And in common usage, the more general a proposition, the more 'scientific' it is regarded to be. For instance, Hayek (1945) contrasts scientific knowledge of 'general rules' with 'knowledge of the particular circumstances of time and place.'

ciated the principle of fixed-wing flight – that propelling a rigid surface through the resistance of air could produce an upward force ('lift') – in 1809. The then revolutionary idea 'freed designers from the previous impractical notion of flapping wings' (Vincenti 1990, 208). Yet, it took nearly a century for the first controlled flight of a powered, heavier-than-air aircraft (when the Wright Flyer flew 200 feet in 17 December 1903) because the practical implementation of Cayley's principle required solving numerous problems and sub-problems of designing wings, airframes, propellers, and flight controls. Designs incorporating the solutions were inevitably complex and epistemically heterogenous: they drew on concisely codified science, detailed engineering know-how, and tacit craft knowledge.

Satisfying several objectives under a range of circumstances contributes to complexity. For example, design objectives for aircraft typically include specifications for 'performance' (e.g. for speed, range, fuel efficiency and payload capacity) and for 'flying qualities' (the ease and precision with which pilots can control an aircraft). Designs must also permit safe landings and takeoffs under conditions of limited visibility, rain or snow and extreme heat and cold, and withstand lightning and bird strikes in flight. Therefore, where feasible, designs include shields to protect artefacts from external vagaries (Nightingale (2004) and Nelson (2008)). Computers for instance have casings to protect their delicate electronic innards, and designs of the plants manufacturing the innards include enclosures to control variations in temperature and exclude dust particles inside the plant.[3]

Eclectic testing of complex recipes

Complexity of recipes makes their testing complex. Recipes for hard boiled eggs may be developed through a simple 'vary time, test firmness' sequence. But chefs developing recipes for French omelettes that can be stuffed with a variety of ingredients whose qualities span a variety of dimensions cannot rely on simple tests. Rather, developers of complex recipes use an eclectic combination of tests.

Such multifarious combinations have a profoundly different character from decisive experiments undertaken to test binary truth values of concise scientific propositions – although technologists and scientists may use the same instruments and techniques such as microscopes, spectrometers, and, as we will see, computerized simulations.[4] Initial tests of new designs might try to establish the basic principles. Modern drug development, for instance, typically starts with tests to identify 'targets' to disrupt the progression of a disease. Subsequent tests progressively narrow possible recipes, balancing expected accuracy against cost and speed. For instance, drug development normally starts with relatively cheap and quick *in vitro* tests of potentially therapeutic molecules and then proceeds through increasingly costly and time-consuming *in vivo* tests, experiments on animals, and finally human trials. Similarly, in Vincenti's (1990, Chapter, 5) case study, theoretical calculations of propeller designs made at negligible marginal cost and low-cost wind-experiments on scaled down propellers in wind-tunnels preceded tests of a smaller number of full-scale models.[5]

Role of judgement

Tests to narrow and select recipes produce more ambiguous results than scientific tests designed to verify sharply defined propositions. The ambiguities in turn dictate subjective judgements about suggestive results. For example, the first heart lung machines were initially tested on dogs and then used in operations on critically ill patients. Although mortality rates were high, published reports included the assessment that the heart-lung machine had functioned well (Fye 2015, 225) encouraging its further use and development. Pharmaceutical testing spans lab and animal

[3]Recipes must also include instructions about sequence – the steps through which a dish is cooked. In contrast, scientific knowledge often focuses on equilibrium states and tendencies (Knight 1921, 17). And, technical recipes are themselves dynamic: Feedback effects and exogenous changes also preclude the timelessness that science aspires to. For instance, the evolution of drug resistant bacteria, patent expirations, and new biosynthesis techniques can spur the redesign of antibiotic molecules.

[4]Classic decisive tests include Newton's prism experiment showing that white light comprises many colours and Pasteur's flask experiment refuting the spontaneous generation of microbes.

[5]The later stage tests may not validate earlier findings. Theoretical calculations of propeller performance deviated significantly from the results of wind-tunnel experiments on scaled down models which in turn did not closely match results from full scale models. Similarly, in medical research animal experiments do not reliably predict what happens in humans. For example, the 'Vineberg procedure' to treat coronary disease which had been refined and tested on dogs proved ineffective in humans. Conversely contrast agents which were dangerous when inserted into the coronary arteries of dogs were accidentally discovered be safe for humans, paving the way for cardio-angiography (Bhidé, Datar, and Villa 2019).

experiments and human trials that (according to DiMasi, Hansen, and Grabowski 2003) require total out-of-pocket costs of over $400 million per new drug approved. The FDA regulates the trials to maximize scientific validity; yet, its expert panels finally judge safety, efficacy and appropriate 'indications' (for drugs that do not demonstrably fail the trials).

Judgements play a similarly pivotal role in choosing which tests to use. For instance, quicker and cheaper software simulations have replaced physical models in the design of bridges and buildings. Medical researchers are switching from laboratory rats and mice to zebra fish: the fish breed more quickly and are easier to care for, while their cell-physiology is like that of humans, making the fish a suitable model for many human diseases (University of Alabama 2016). Developers of consumer goods on the other hand now increasingly favour more laborious 'ethnographic' research over traditional market surveys and interviews (Madsbjerg and Rasmussen 2014). And adoption of new tests usually turns on judgements. Zebra fish may be demonstrably cheaper, but their reliability for testing new treatments of human disease is based on fallible inference. Likewise, the increasing use ethnographic research is based on *prima facia* plausibility and some success stories.

Technologists have more leeway to exercise such judgements than scientists who are constrained by the testing conventions of their communities. For instance, some architects prefer traditional physical models to evaluate building designs over cheaper, faster, and now more popular computer simulations. Some developers with unusual confidence and authority, like Steve Jobs, may rely on their instincts instead of market-research. Others may favour 'on-line' beta testing and trial and error ('learning by doing' experimentation) to ex-ante, 'off-line' tests. Technologists' tests are therefore more eclectic than scientists' tests; there is also greater diversity of the combinations used.

II. Practical limitations of economic science

Scientific orientation of goals and methods

Disciplinary economics, which Hands (2001) distinguishes from 'ersatz economics, Better Business Bureau economics, or folk economics,' has long favoured scientific knowledge and inquiry. The first sentence of Frank Knight's 1921 classic, *Risk, Uncertainty and Profit* tells us that economics is 'the only one of the social sciences which has aspired to the distinction of an exact science' like physics.[6] And like physicists, economic scientists prize propositions that transcend specific circumstances. Knight (1921, 3) asserted that 'the very conception of an exact science involves abstraction' while Friedman (1953) argued that an 'important' hypothesis '"explains" much' by abstracting 'crucial elements from the mass of detailed and complex circumstances.' Nowadays, writes Cartwright, 'modelling by the construction of analogue economies is a widespread technique.' The models, popularized by and closely associated with Robert Lucas, 'have only a few agents with few options and only a narrow range of both causes and effects is admitted.' The goal is to 'isolate [a] process; to study it in a setting where nothing else is going on that might affect the outcome as well (Cartwright 2007, 222).'[7]

Disciplinary economists, like other scientists, value decisive verification to each other's satisfaction. And, as in other scientific communities, standards for verification evolve. John Stuart Mill (1874), who categorized economics as an *a priori* deductive science, and later Knight, called themselves 'empiricists' in the sense of 'holding that all general truths or axioms are ultimately inductions from experience (Knight 1921, 8).' Mill and Knight also saw theories predicting 'tendencies' that might be confounded by extraneous factors without refuting the theory proposed.[8] Rather, their main criteria for validity was whether the initial premises conformed to experience and whether tendencies deduced logically followed.

[6]In 1968 the Swedish central bank endowed the 'Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel.' None of the other Nobel prizes include 'science' in their name and indeed physics and chemistry awards periodically recognize instruments and artefacts that, like the Boyle-Hooke air pump, mark significant engineering achievement. For example, Arthur Ashkin shared a Nobel prize in Physics in 2018 for developing 'optical tweezers' and all three Chemistry prize winners in 2019 were recognized for developing lithium-ion batteries.

[7]Even economists who study institutions abstract away from the particulars. Seminal papers on transaction costs (e.g. Coase 1937) or legal origins (e.g. La Porta et al. 1998) utilize broad categories such as 'firms' and 'markets' and 'civil law' and 'common law' systems. Elinor Ostrom's case-study-based heuristics for solving commons problems stand out in their exceptional attention to specific institutional circumstances (and, as pointed out by this paper's referee, to decision-making processes).

[8]Specifically, Mill defined economics as a science concerned solely with the conduct of man *'as a being who desires to possess wealth'* and that 'predicts only such of the phenomena of the social state as take place in consequence of the pursuit of such wealth (Mill 1874).' But because people had other desires the predictions could not be clearly observed.

Deductive theorizing is now almost invariably mathematical.[9] This enables verifying the internal consistency of elaborate analogue models (mentioned above) in which everything is fully and precisely specified. Meanwhile 'empiricism' has also changed from using personal experience as the starting point for causal theories to testing predicted outcomes (as Friedman (1953) had advocated) and using sophisticated econometric methods to exclude the effects of extraneous factors and spurious correlations.

Limitations of deductive theories

According to Lucas, analogue models that produce 'statements of verifiable [deductive] fact' can serve 'as laboratories in which policies that would be prohibitively expensive to experiment with in actual economies can be tested out at lower costs.' Artificial conditions are not deficiencies Lucas observes: 'Any model that is well enough articulated to give clear answers to the questions we put to it will necessarily be artificial, abstract, patently "unreal" (Lucas 1981, 271–272),'

Cartwright agrees that analogue models can have practical utility: it may be helpful for policymakers to learn from Pissarides's model how skill loss can make unemployment persistent, even if factors excluded from the model offset this tendency. Nonetheless, three reasons warrant caution about relying just on analogue and other such deductive models to evaluate new policy recipes.

First, although the number of agents, options, causes, and effects admitted in the models are few, 'the list of assumptions specifying exactly what the analogue economy is like is very long' (Cartwright 2007, 226). The Pissarides skill-loss model 'contains some 16 assumptions and that for just the first of six increasingly complex economies that he describes' (Cartwright 2007, 228). And we cannot know whether the tendency of interest (e.g. the persistence of unemployment) arises from the causal mechanisms the model seeks to isolate or from the many incidental or auxiliary assumptions used to make the model deductively verifiable. We may therefore learn little about tendencies outside the analogue economy. Additionally, modelling requires 'special talents and special training,' potentially excluding contributions from 'different kinds of thinkers who may provide different kinds of detailed understanding of how economies can and do work' (Cartwright 2007, 234).[10]

A second problem with the practical application of deductive models arises from aggregation that obscures important parts of the whole. Central bank economists for instance now rely heavily on models in which everyone produces and consumes the same thing. But, as Mervyn King pointed out in a July 2017 lecture at the National Bureau of Economic Research, policies to sustain demand for consumption as a whole can injure producers of goods exposed to international competition. Similarly, before 2008, the US Federal Reserve's model did not have a financial sector and thus did not consider the risks of its collapse.[11]

A third problem pertains to the difficulty of combining the results of models that admit 'only a narrow range of both causes and effects.' An airplane designer can use Newton's laws of motion and fluid flow equations to separately estimate the forces of gravity, lift, and drag and then cumulate their overall effect using vector addition. Similar procedures do not exist in economics. Therefore, one model may help estimate the effect of easing monetary policy and a different model may provide estimates of the effects of increasing capital requirements for banks. But adding up the two estimates does not provide a useful prediction of the overall outcome.

More complex models might ameliorate the second and third problems. For instance, models might distinguish between tradables and untradables, between services and manufacturing, and include a banking sector and bank capital requirements. But greater complexity would require more incidental assumptions, making it harder to isolate tendencies of interest to policymakers. Or they might fail to yield unique solutions and therefore sacrifice the 'statements of verifiable fact' valued by Lucas.

[9]Belying Knight's prediction that 'mathematical economics ... seems likely to remain little more than a cult (Knight 1921, 14).'

[10]Unverifiable auxiliary assumptions also connect hypotheses to observations and experimental results in the physical sciences. Therefore, scientific falsifiability inevitably requires conventions to justify its procedures, as Karl Popper – the best-known champion of falsifiability – pointed out, (Hands 2001, 92).

[11]In contrast, engineers are expected take seriously the risks of failure of minor components, such O-rings in rockets, and treat the whole only as resilient as its most vulnerable part. In economic science, theorizing (and empirical verification), requires extensive aggregating and abstracting, as mentioned. Kremer's (1993) O-ring theory of economic development itself analyzes highly abstracted constructs.

Limitations of econometric and experimental tests

Econometric techniques to verify causal tendencies through natural experiments and difference in difference testing also have scientific aims that limit practical utility. They can help verify tendencies outside artificially constructed economies listed above. But econometric tests, like physical experiments, require many assumptions that conform to conventions chosen to coordinate scientific inquiry rather than for their practical utility. Econometric models also follow the scientific convention of focusing on a few abstracted constructs. The practical problems of suppressed detail and of adding the effects of multiple tendencies to evaluate complex recipes therefore remains. Moreover, many important policy choices are naturally novel (e.g. quantitative easing in the US and Europe and privatization in transitional economies); therefore, suitable natural experiments and control groups may not be available to investigate even the general tendencies affecting these choices.

In principle, Randomized Controlled Trials (RCTs) can test novel policy combinations. But, in practice, according to Deaton and Cartwright (2018), 'RCT results can serve science but are weak ground for inferring "what works."' Efforts to mirror the norms of natural science experiments apparently limit utility. *Inter alia* the efficacy of policy interventions – as in engineering and medicine – can depend a great deal on how their constituent ingredients are combined: one combination of the same ingredients can produce spectacular results while another combination can utterly flop. But the cost and time needed for RCTs will typically permit testing only a few possible combinations.[12]

III. Using simulations to support policy judgements

Risks of unilateral and siloed judgements

In practice, policy makers (including those on leave from economics departments) often rely on subjective judgements – choosing 'narratives' as Kay and King (forthcoming) put it – to go beyond standard equilibrium models and empirical tests. But opaque or ad-hoc judgements – the Federal Reserve's qualitative stress tests of large banks or protracted quantitative easing for instance – can expose policymakers to allegations of caprice or favouritism and undermine their legitimacy and public standing. In other instances, regulators avoid the vector addition problem by focusing on narrow remits. But siloed choices can produce intractable misalignments; as with omelettes made from bad recipes, basic inconsistencies cannot be repaired, although the alignment of approximately congruent policies can be iteratively improved. Eclectic 'technological' combinations of tests and contextual judgements that help policy makers reduce the risks of compromised legitimacy and inconsistency therefore warrant consideration.

Simple imitation of engineering or medical practices is clearly impossible. Wind-tunnel experiments and rapid prototyping with foam models are infeasible in economic domains. Conversely, there may be a greater role for collectivized judgement through a dialectical, collaborative – or even formally adversarial – process that integrates consideration of prior cases and precedents with numerical data. Such evaluations are routine in judicial, legislative, and business decisions. But instead of comparing a broad set of possibilities, I focus next on how computerized simulations can support collaborative judgements about novel recipes.

Simulations as collaboration tools

As mentioned, simulation software is now widely used in engineering as a low-cost substitute for physical models to evaluate new designs. Simulation tools available for practical economic applications have also vastly improved. Many hedge funds for instance use sophisticated Monte Carlo simulations for pricing assets and managing portfolio risks. And, virtually all businesses use spreadsheet simulations, not closed form equilibrium models, to evaluate and plan projects.

The widespread use of spreadsheet simulations likely reflects multiple benefits that offset the

[12]Critics of RCTs of surgical innovations have long highlighted the problem of variants. For instance, Love (1975) questioned the value of randomized trials of bypass operations, and other evolving procedures, noting that surgical operations were 'rarely introduced as fully defined, easily reproducible techniques.' Rather, they came as 'principles for solving particular problems' that could be implemented in a wide variety of ways. For instance, more than 200 specific procedural combinations could be used for the same general principle of heart valve replacement. (See Jones 2000 and Bhidé, Datar, and Villa 2019 for more complete reviews of the unresolved controversy about coronary bypass trials.)

limitations. As with most physical artefacts, several choices (about for instance pricing, advertising, compensation, and borrowing) combine with external factors (such as demand, wages and interest rates) to produce many consequential outcomes (such as profits, cash flows, and shares of strategically important markets). Spreadsheets provide a convenient way to model and display how multiple choices might map into multiple outcomes, mitigating the 'vector addition' problem mentioned earlier.

The models are however entirely 'deductive,' and their premises invariably speculative. Spreadsheets require specifying many individual functional relationships (e.g. how consumers respond to prices and advertising) whose structural forms and parameter values are not easily observable and are highly context specific. Their value lies in conveniently projecting what happens under different guesstimates. Even models with questionable guesstimates – and wide ranges of outcomes, exemplified by Sahlman's (1990) discounted cash flow calculations – can serve as 'conversation pieces' for discussions that may improve and confer more legitimacy to judgements than would purely verbal reasoning.

The discussion and legitimacy are especially valuable in pooling diverse expertise and opinions to evaluate large irreversible investments undertaken by professionally managed organizations that separate decision-making and decision control (Fama and Jensen 1983) – even though the reliability of the spreadsheet projections is obviously low.

In the public sector, spending agencies use spreadsheets to evaluate infrastructure projects. Bank regulators and bank compliance officers use simulations in Internal Rating Based (IRB) calculations of bank capital requirements; regulators also use Monte Carlo simulations to monitor the trading and systemic risks of hedge funds; and, in 2010 the European Commission formalized SYMBOL (Systemic Model for Banking Originated Losses) simulations as the standard for testing proposed financial regulations and rules including deposit insurance schemes, bank capital requirements, and financial transaction taxes.

Published research on simulations

Some of these regulatory initiatives have produced scholarly and semi-scholarly research publications. Many regulators and their consultants who work on simulations have PhDs in economics – and some have faculty appointments in economic departments. And unlike private companies who worry about confidentiality, regulatory agencies often encourage the publication of staff papers, books, and journal articles.

For instance, European simulation-based publications include Galliani and Zedda (2015) and Benczur et al. (2016) on bail-in and bail out rules; Cannas et al. (2014) on transaction taxes; and, Marchesi et al. (2012) and De Lisa et al. (2011) on deposit insurance. Publications sponsored by the U.S. Office of Financial Research (OFR) that use simulations include Flood and Monin (2016) and Flood, Monin, and Bandyopadhyay (2015) on the use of Monte Carlo simulations to monitor hedge fund risks; and, Paddrik and Young (2017), Paddrik et al. (2016a, 2016b), Cetina, Rajan, and Paddrik (2016), and Flood and Korenko (2015) on supervisory stress testing. Other working and staff papers published by the OFR, including Liu et al. (2016), Bookstaber and Paddrik (2015), Paddrik et al. (2014), Bookstaber, Paddrik, and Tivnan (2014), and Bookstaber (2012) assess systemic risk using agent-based modelling.

These publications have antecedents in research from the 1950s when Allen Newell and Herbert Simon 'conceived the idea that the right way to study problem-solving was to simulate it with computer programs' (The Nobel Prize 2019a). By 1960, simulation had gained sufficient traction for the *American Economic Review* to publish a symposium on its use in economics, with contributions by Martin Shubik, Guy Orcutt, and Geoffrey Clarkson and Herbert Simon (Morgan 2004). Nelson and Winter (1982) used computer simulations to model innovation and explicate their evolutionary theory of economic change.

But it would not be unfair to say that simulations, and especially their practical applications, fall outside the disciplinary mainstream. PhD coursework in economics (which Hands uses as a criterion for demarcating the discipline) rarely includes learning about simulation software. In contrast, spreadsheet simulations are routinely used to teach quantitative analysis in all graduate and undergraduate business programmes. And engineering students learn to use more advanced simulation tools, such as Matlab, Python, and SimPy, through lectures, textbooks (such as Nelson 2013) and course-projects.

Simulations are likewise now rarely seen in leading journals in economics and finance, compared to say difference-in-differences estimations, possibly because simulations cannot easily satisfy scientific standards for generalizability and replicability. Moreover, disciplinary economists doing scientific research predominantly use (and have previously used) simulations to investigate concise general propositions, not multifaceted contextual prescriptions. (Knudsen, Levinthal, and Winter (2017) and Bazdresch, Kahn, and Whited (2017) exemplify recent scientific use.)[13]

Controversial popularity of field experiments

RCTs have attracted much greater support and controversy. The US Congress initiated regulatory use of randomized trials in 1962 when it authorized the FDA to secure 'substantial evidence' of efficacy to approve new drugs. Over time the FDA required randomized multi-centre trials 'with clear, prospectively determined clinical and statistical analytic criteria' (FDA, 1998, 12). The US government used trials to evaluate economic policies in the late 1960s and 1970s when it 'sponsored four large-scale social experiments to measure individuals' responses to different levels of benefits and tax rates' (Munnell 1986, 1).

Starting in the 1990s, RCTs 'transformed development economics' as the 2019 Nobel Prize in Economic Science announcement noted (The Nobel Prize 2019b). According to Pritchett (forthcoming) 'there are now literally thousands of published RCTs, with dozens of studies on conditional cash transfers, on micro-finance, and literally hundreds of studies of boutique interventions in water, sanitation, education, health [and] business training.' Pritchett questions their actual impact however and Bédécarrats, Guérin, and Roubaud (2020) report that the budget for 'a classic RCT is between $500,000 and $1,500,000, and each RCT often generates just one published research paper.' Moreover, whatever their cost-effectiveness, scientific RCTs can only provide a starting point for complex recipes (as argued in section 2.3 above).[14]

I will illustrate how simulations – which we can think of as cheap 'virtual' experiments – can help evaluate policy recipes through the example of rules that affect how lenders screen loan applicants. Unlike scientific simulations and RCTs, this illustration does not seek to validate or refute general propositions. It also does not propose specific prescriptions (whose efficacy, as with most practical recipes, will depend on circumstances of time and place). Rather, the example illustrates how low-cost simulations can support judgements about combinations whose complexity and novelty limit what decision makers can learn just from theoretical models, econometric studies, and RCTs.

My aim is analogous to showing how spreadsheets can help design programs to launch new products rather than to produce scientific propositions about new product launches. And, consistent with this limited purpose, my simulations make illustrative assumptions about 'input' functions and numerical values and produce 'outputs' that merely exemplify how simulation results can facilitate discussion and judgement. The illustration does not however target an imaginary gap in evaluations of policy outcomes, as we will next see.

IV. Simulation model for credit screening

Policies affecting credit screening

Credit intermediaries (that I will for convenience call 'lenders' even though they may simply originate loans for sale to investors) routinely seek to screen out unscrupulous or overconfident borrowers using categorical markers, statistical models, and information about individual applicants. Regulatory choices in turn affect lenders' choices about the nature and extent of their screening. For instance, anti-discrimination laws in the US forbid lenders from using borrowers' postal codes to screen loan applications and, as described in Bhidé (2017), promote strict reliance on credit bureau scores by increasing the regulatory risks of securing more detailed information. European rules in contrast do not prohibit rejections based on postal codes and new rules now encourage lenders to secure detailed information by making the lenders liable for loans carelessly made to borrowers who fail to repay.

[13]Simulations typically used in scholarly economic research are analogous to simulations used to design experiments in high-energy physics and biologists' evolutionary models rather than simulations used by engineers to design bridges and buildings.

[14]For instance, the Prize Committee for the Economics Nobel praised the 2019 winners for RCTs showing that distributing more textbooks without better teaching did not improve student learning and that paying bonuses reduced teacher absenteeism, when attendance was monitored by cameras. Such demonstrations may provide valuable general cautions about of the importance of complements and incentives; but, reminders to buy eggs and butter doesn't tell cooks how to make tasty omelettes. And, policy recipes have to match specific circumstances: RCT studies of paying US professors bonuses (with CCTV monitoring) to reduce their absenteeism might fail Institutional Review Board scrutiny. But, million-dollar RCTs can screen just a few of many possible combinations for fit with their targeted circumstances.

Regulators also have indirect influence: increasing capital requirements is believed to encourage more careful screening; conversely, promoting competition between lenders can limit their willingness and capacity to pay for information about borrowers – or possibly spur more efficient screening.

Assessing the overall effect of these policy combinations is however difficult. Canonical models reviewed by Fisman, Paravisini, and Vig (2017) for instance suggest that while policies that encourage lenders to secure more information will tend to reduce rates and losses, the effect on the quantity of lending is ambiguous. And, the 'vector addition' problem mentioned earlier makes it difficult to assess disparate combinations – how might for instance changing capital requirements and anti-trust rules along with information requirements affect loan rates and volumes? Similarly, as also mentioned, new policy combinations increase potential errors produced by applying empirical results drawn from historical data. And, verbal reasoning alone does not take us far.

Yet after 2008, policy makers have made significant changes on several fronts. As mentioned, European regulators have increased penalties for careless credit extension but have also sought to increase competition between lenders (potentially reducing their capacity to pay for more screening). In the US, regulators have increased 'know your borrower' requirements, but to a lesser degree than in Europe. At the same time, US regulators have 'gold-plated' internationally agreed-on capital requirements. How these new policy combinations are likely to affect lending is therefore not just a hypothetical question.

SYMBOL simulation protocols could be used to assess the combinations but have not. Simulation studies sponsored by regulatory agencies have apparently focused more on specific interventions, such as capital requirements and deposit insurance rather than their 'combinations' (e.g. increased capital requirements plus more pro-competition rules). In particular, simulations appear not to have investigated combinations that include rules requiring or discouraging lenders from collecting information about borrowers. They also seem to focus more on systemic risks rather than routine lending effects.

The effect of policy combinations on securitization also remains unexamined. Bhidé (2017, 2019b) suggests that US rules discouraging lenders from collecting detailed information enable exceptionally high securitization: As lenders' ignorance increases investors' concerns about information asymmetries decline, although overall defaults by borrowers increase. And, reducing the 'lemon' risks increases the demand for 'pooled' securities, provided borrowers in the pool pay interest rates commensurate with the higher defaults produced by less informed lending. If this hypothesis is correct, European efforts to raise securitization to US levels without imposing similar limits on lenders' information are unlikely to succeed.

But, capital requirements on loans held to maturity also encourage securitization (Bernanke and Lown 1991). Could tougher capital requirements, rather than less severe information asymmetry problems, account for the exceptionally high securitization of credit in the US? If so, European policymakers could plausibly expect to boost securitization while also encouraging lenders to secure more information about borrowers (by raising capital requirements). This possibility too has not been researched either through simulations or traditional equilibrium models and econometrics.

Main features

My simulations show that under illustrative assumptions, combining rules requiring in-depth credit analyses of borrowers with tougher antitrust rules will: 1) increase interest rates, 2) reduce loan volumes, and 3) severely discourage securitization. The simulations also provide indicative 'guesstimates' about magnitudes, again under illustrative assumptions.

Like Bain's (1959) 'structure-conduct-performance' paradigm my model does not contain 'policy' variables (See Table 2). Rather, as in the Bain model, it can help generate plausible hypotheses about how policies that likely affect 'structure' and 'conduct' variables could alter lending 'performance'.

I make two simplifying assumptions about the two 'conduct' variables. I assume that lenders incur the same expenditures to screen all the loan applications they receive, denoted by the variable *InfoCost* and expressed as a proportion of loan applications. For instance, if lenders spend $5 to screen $100 of loan applications, *InfoCost* will equal 0.05. Similarly, I assume that lenders offer all applicants they categorize as creditworthy loans at the same *PrimeRate* and all other applicants' loans at the same *NonPrimeRate*.

Table 2. Model variables and mapping assumptions.

Structure: Exogenous Conditions	*Conduct*: Lenders' Choices	*Performance*: Lending Outcomes
• Market power of lenders (capacity to charge profit maximizing interest rates) • Proportion of loan applications submitted by creditworthy borrowers • Efficiency of lenders' spending on information collected to screen applicants • Rate sensitivity of loan applicants • Loss incurred by lender per dollar lent to bad borrowers • Capital cushion lenders maintain as buffer against unexpected losses and the cost thereof	• Expenditure on information to select 'good' or 'prime' borrowers. • Interest rate on loans offered	• Loans made and profits earned • Unwarranted approvals and rejections of loan applications (Type I and II errors) • Whether loans securitized

Some 'structural' variables in the first column may not be entirely exogenous: for instance, lenders may increase the proportion of creditworthy borrowers and the efficiency of their screening by only considering applicants with whom the lenders have long standing relationships. Or they may reduce losses on bad loans by requiring borrowers to post significant collateral. However reclassifying these exogenous conditions as choice variables has no effect on the utility of the simulation model in evaluating policy combinations. Similarly, treating lenders' choices of interest rates and as a 'performance' variable is also practically inconsequential.

The model, implemented (as described in detail in Appendix 1) through a personal computer-based software program called *Mathematica*, also includes two sets of 'mapping' assumptions that specify how:

- *Expenditures on information by lenders affect their screening accuracy*. I assume an S-shaped function such that increasing expenditures increases accuracy in identifying good and bad applicants from negligible to perfect.
- *Interest rates on loan offers affect proportion of offers accepted*. Here I assume an inverse S shape, with negligible acceptance at high rates and complete acceptance of zero-interest offers.[15]

Alternatives and complements

As in all simulations, my model requires starting with a mathematical representation of variables and assumptions about their parameters. And, including many variables, which allows examination of policy combinations, precludes unique analytical solutions. Rather, projecting outcomes requires assuming specific numerical values for some variables and the visual examination of plots. And, because like 'business' spreadsheets, my simulations are entirely deductive, using different mathematical representations or making different numerical assumptions would change the results. Moreover, the complexity of multi-variate simulations poses expository challenges.

But practical applications of closed form equilibrium models, which in principle produce unique, unambiguous solutions cannot avoid these problems. For instance, Black-Sholes-Merton option pricing models produce results that are highly sensitive to unverifiable, subjective assumptions about the volatility of the prices of the underlying securities. These cannot be reliably inferred from historical prices: for instance, there is no theoretical basis for using 30-day prices rather than 90-day prices to calculate historical volatility and historical volatilities can be unreliable predictors of future volatilities (Bhidé 2010, 137). Moreover, for many users of option pricing models, the mathematics can be 'off-putting' according to Mackenzie 2008, 163), making crucial auxiliary assumptions opaque to the users.

Yet, Black-Sholes-Merton option pricing models play an important practical role by providing a common 'vocabulary' to traders and their managers (Mackenzie 2008, 163) who may have different views about future volatilities. The vocabulary in turn enables more objective discussions that, as mentioned earlier, give legitimacy to judgements made and can help exclude some utterly implausible options. My illustrative simulation similarly seeks to support discussions about policy combinations that cannot be evaluated with closed form equilibrium models.

Unlike axiomatically based option pricing models, my simulations do reflect ad-hoc choices of salient variables, functional forms, and numerical values. But implementing the simulation in *Mathematica* allows analysts to easily change the variables, functions, and numerical values to reflect their judgements about conditions in specific credit markets. In contrast,

[15]The two assumptions embody similar intuitions and limits: small changes in expenditures on information aren't likely to affect accuracy when spending is close to zero or already very high. Similarly, small changes in interest rates won't attract or discourage many more borrowers when rates are close to zero or very high. And, as defined, the values of both variables cannot exceed 1 or fall below zero. S shaped functions satisfy these conditions.

modifying the Black-Scholes-Merton model (or the Pissarides skill-loss model mentioned earlier) without breaking their capacity to produce unique solutions requires extraordinary expertise and skill.

In principle, a spreadsheet would require even less skill to modify than my *Mathematica* model; but, in practice, the complexity of a spreadsheet (with the functionality of my simulation) would make changes difficult to implement and audit. Additionally, although using *Mathematica* requires learning the program's syntax, the software has more powerful analytical, computational and plotting capabilities than spreadsheets. This has for instance allowed me to use a built-in logistic function to specify an S-shaped relationship between lenders' spending on information and the accuracy of screening (and an inverse S-shape for borrower response to interest rates). Analysts can try alternative specifications by changing one or two lines of the code: the logistic specifications can be replaced with an exponential decay function, for instance. Adding or substituting variables to analyse additional policy combinations is also relatively simple. And, *Mathematica* allows easier plotting of more complex possibilities than would spreadsheets.

My model does not however include dynamic or interactive effects: borrowers don't learn or change their behaviour; competing lenders don't adapt to each other's strategies; and, changing the value of one of my 'structure' variables does not affect the value of any other. It also generates end results without indicating the path followed to get there; and, paths can be of serious concern to policy makers. But it is hard to imagine any equilibrium or spreadsheet model without similar limitations.

An agent-based model could incorporate some dynamic and interactive effects that my simulations lack and trace paths along which the variables change. But the results of agent-based models can depend on how long the models are run for. The models are also more complex and require more expertise to construct and modify, potentially limiting their transparency and value in discussing and legitimizing policy choices. Agent-based modelling may however serve as a useful complement or a 'next step' to my simpler simulations (in the same way as *in vivo* tests might follow *in vitro* tests in pharmaceutical research or wind tunnels follow simulations in aeronautical design).

V. Illustrative plots and policy implications

Regulating information and competition

To focus on the joint effects of regulating information and competition on lenders' 'conduct' (choices) and thus on lending 'performance' (outcomes) I first fix five 'structure' (exogenous) variables in the base-case of my simulation model as follows:

'Structure' Variables: Definitions and Base Case Values

Variable	Definition	Value assigned[16]
GoodProportion	Loan applications submitted by creditworthy borrowers expressed as a proportion of total loan applications.	80%
CapitalCost	Cost incurred by lenders to maintain a capital buffer against losses, expressed as a proportion of the monetary amount of total loans made.	1%
Loss	Loss on loans made to borrowers who are not creditworthy, expressed as a proportion of the monetary amount of loans made to such borrowers.	50%
RateSenstivity	Parameter of function mapping interest rates offered by borrowers into acceptances of loan offers.	20
InfoEfficiency	Parameter of function mapping costs incurred by lenders to screen applicants into accuracy of screening.	200

I then compute interest rates as a function of *InfoCost* under two kinds of market structures: 1) Monopolistic, when lenders set rates to maximize profit, and 2) Highly competitive, when lenders maximize loans by charging 'break-even' interest rates (that allow lenders to avoid losses). Expectedly, as shown in Figure 1, the profit maximizing interest rate (charged by lenders with market power) is always greater than the breakeven rate.

Ideally, we would next want to find an expression or value for the lenders' optimal spending on screening expenditure (*InfoCost)*, but the model's complexity makes such a computation impossible. The software can however plot (Figure 2) several lending outcomes – the 'performance' variables of potential interest to a policy maker – as a function of the lender's choice of *InfoCost*.

[16]In practice, analysts would be able to estimate the values with varying degrees of confidence. *CapitalCost* would be known. *Loss* and to some degree *GoodProportion* might be estimated from historical data. *RateSensitivity* and *InfoEfficiency* would be guesses and therefore the top candidates for sensitivity testing of the simulation results.

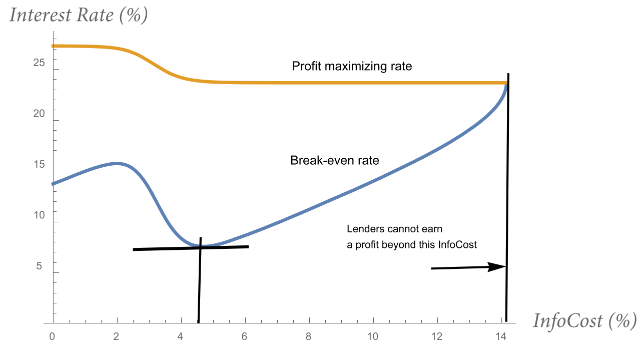


Figure 1. Interest rates as a function of Information Expenditures.

The Figure 2 plots (below) suggest the following relationships between policy goals and combinations of market structure and *InfoCost* policies:

- If regulators want lending to all good borrowers and zero to bad borrowers, their rules should *maximize* competition between lenders and *require* spending of about 5.7% (of the value of the loan applications screened) on *InfoCost*.
- If regulators want 'prudent' oligopolist lenders to earn profits (as a cushion for future credit shocks) – but lend nothing to bad borrowers, the rules should *limit* competition but *require* lenders to spend about 5.7% on *InfoCost*.
- If regulators *limit* competition and *do not regulate InfoCost* expenditures, lenders will *choose* 4.5% *InfoCost*, producing a 1% rate of lending mistakes (bad applicants receiving loans and good applicants not receiving loans).
- *Requiring* lenders to spend 4.5% on *InfoCost* while *maximizing* competition will minimize interest rates borrowers pay.
- Requiring lenders to spend *less* than 4.5% on *InfoCost* while *maximizing* competition will increase total lending – and the rates borrowers pay (as compared to unregulated spending on *InfoCosts).*

The plots also suggest that the current US combination of an oligopolistic banking structure with severe restrictions on *InfoCost* has the unintended consequence of (compared to the other combinations plotted) maximizing interest rates borrowers pay, while minimizing good loans and their percentage of loans made. Similarly, current European efforts to increase competition in banking while imposing tough 'know your customer' rules may be neutralizing each other, at least in terms of increasing lending: competition reduces interest rates and increases loans made; but high spending on *InfoCost* has the opposite effect.

Non-prime prime rates and prime securitization

As detailed in Appendix 1, lenders may extend offers at non-prime rates to applicants who they have characterized as 'bad,' under the expectation that some of these applicants may in fact be creditworthy. But, if lenders incur large information expenditures in their initial screening, few good applicants will be left in

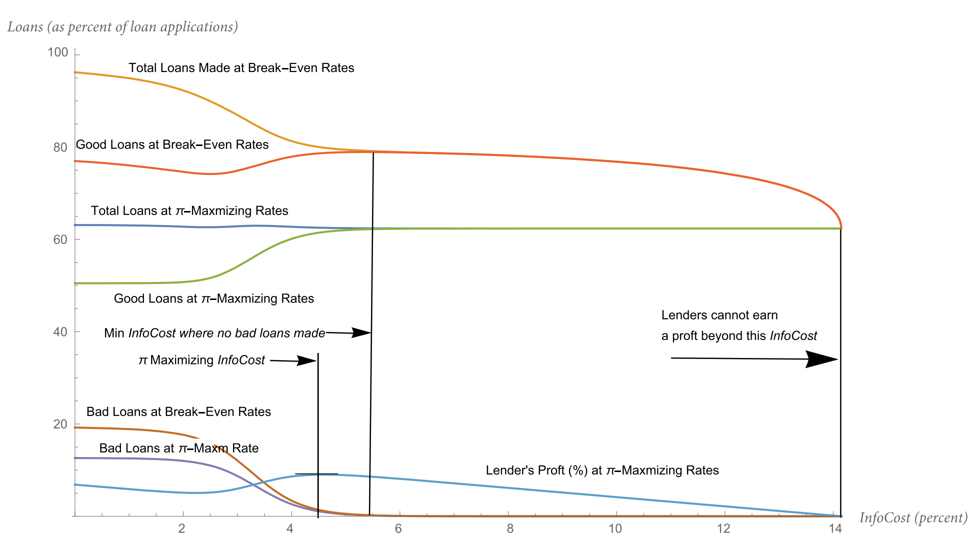


Figure 2. Loans made and Profits earned as a function of information expenditures.

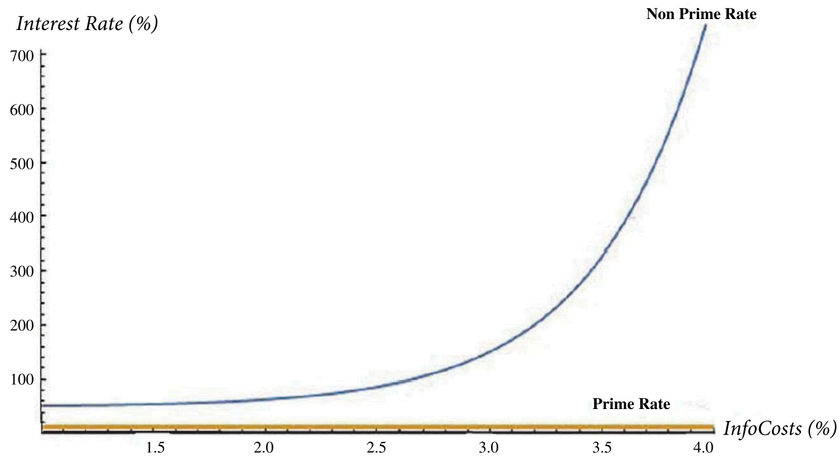


Figure 3. Prime versus non-prime interest rates.
Note: Plot for Prime Rate same as in Figure 1 but highly 'flattened' because of different Y-axis scale

their 'reject' pool. Therefore, as shown in Figure 3, lenders will offer non-prime loans at much higher rates than they offer prime loans. And at high sub-prime rates many borrowers will reject loan offers. The plot thus suggests that rules that allow or require high spending on information will severely limit or even eliminate sub-prime lending.

The plot also provides an indication of the extent to which differences in US and European rules affect securitization. As mentioned in Section 2.1 (and in Bhidé 2017, 2019b), capital requirements encourage banks to securitize their loans while 'lemon' problems hinder securitization. US rules limiting information also limit the 'lemon' problem hindrance: lenders offer loans to all applicants whose credit scores (generated by a credit bureau, rather than the lender) exceed a threshold without any further scrutiny. The lender thus has little information to hide from buyers of its securitized loans. In contrast, European rules, which require more information gathering, mean that European banks know more about the creditworthiness of each borrower. This increases investors' concerns that lenders will sell off their bad, non-prime quality loans while keeping their good, prime quality loans. Investors may then demand rates commensurate with the quality of non-prime loans. The higher rates, the plot suggests, can run into triple digits, severely discouraging securitization and overwhelming any plausible capital costs benefit the bank might gain.

Effects of policies affecting other structure variables

Regulators can influence the 'structure' variables whose values I had fixed earlier (for the 'base-case' Figure 1–3) in several ways: capital requirements directly affect *CapitalCost*s; rules such as the US Community Reinvestment Act that require lending in economically distressed neighbourhoods can potentially reduce *GoodProportion* (the proportion of creditworthy applicants); bankruptcy rules protecting delinquent borrowers can increase *Loss* (by reducing what lenders can recover from defaulted loans) and reduce *RateSensitivity* (by increasing the willingness of borrowers to take on high-interest obligations); and rules to increase competition by reducing borrowers' switching costs may reduce *InfoEfficiency* (because lenders now screen applications submitted by non-customers).

Changing the values of the structure variables in my model can provide hypotheses about the effects of such interventions as discussed in Appendix 2. As before, the hypotheses pertain to the particular values used in my illustrative example, not what we can expect as universal occurrences or tendencies. And, even careful studies of specific circumstances will not yield foolproof estimates of the necessary values. Indeed, a noteworthy generalization suggested by the illustration is that like the comparative statics of parsimonious equilibrium models, simulations cannot by themselves predict the concrete effects of multifaceted policy changes. Novelty and complexity make Knightian uncertainty unavoidable and eclectic techniques and interpretive judgements necessary.

VI. Concluding comments

Milton Friedman took his distinction between 'positive' economic and 'normative' ethical questions from what he called John Neville Keynes's 'admirable book, *The Scope and Method of Political Economy* (Friedman 1953).' But, while Keynes's 1890 book – like Friedman's later essay – highlighted the problems of confusing the positive and the normative, Keynes also distinguished the positive science of economics from 'the system of rules for the attainment of a given end,' which he called its 'art.'

Systematic medical and engineering art has made great advances since the publication of Keynes's book. We can credit an important part of this progress to foundational advances in scientific knowledge, but engineering and medicine have also benefitted enormously from efforts to develop technological tools. In economics however, disciplinary effort has strongly favoured systematic science over systematic art.

Alvin Roth's (2002) 'Economist as Engineer' paper on the development of labour clearing houses that place doctors in their first jobs, auctions of the radio spectrum, and markets for electric power, illuminates an instructive exception. Economists followed an 'engineering approach,' Roth writes, that combined game theory, computation and experimentation and took responsibility for details and complications. These efforts and subsequent programs to match students and schools and kidney donors and recipients have produced indisputably significant practical results.

The exceptions may have benefitted from unusual circumstances: game theory that provided an atypically comprehensive conceptual foundation; computational tools and rapid 'lab' experiments that enabled the development of design details at a fraction of 'field' RCT costs; interactions of users that (like the innards of computers and semi-conductor plants) could be shielded from external disturbances; and economists (such as Roth and Vernon Smith) who, like the Manhattan project's physicists, had extraordinary talents for science, invention and enterprise.

In an alternative view, techniques for computational experimentation now widely used in medical research have surged ahead. Several other techniques (reviewed in Bhidé 2019a)[17] also now support the design of complex artefacts and procedures. Prominent economists are using and improving the computational and other tools in private companies – Hal Varian at Google for instance. But like medieval artisanal knowledge (developed before 'open' engineering research), valuable advances made in private companies often remain confidential. Meanwhile, dedication to scientific propositions and methods limits the practical contribution of more 'open' disciplinary economics. Valuing practical ends, alongside Friedmanite science, and tolerating eclectic technological means would give Roth's economist-engineer more scope to advance the common good.

Disclosure statement

No potential conflict of interest was reported by the author.

References

Bain, J. S. 1959. *Industrial Organization*. New York: Wiley.

Baldwin, C. Y. 2018. "Design Rules, Volume 2: How Technology Shapes Organizations: Chapter 7 the Value Structure of Technologies, Part 2: Technical and Strategic Bottlenecks as Guides for Action." Harvard Business School Research Paper Series No. 19-042.

Bazdresch, S., R. J. Kahn, and T. M. Whited. 2017. "Estimating and Testing Dynamic Corporate Finance Models." *The Review of Financial Studies* 31 (1): 322–361. doi:10.1093/rfs/hhx080.

Bédécarrats, F., I. Guérin, and F. Roubaud. 2020. *Randomized Control Trials in the Field of Development: A Critical Perspective*. Oxford: Oxford University Press.

Benczur, P., G. Cannas, J. Cariboni, F. Di Girolamo, S. Maccaferri, and M. Petracco Giudici. 2016. "Evaluating the Effectiveness of the New EU Bank Regulatory Framework: A Farewell to Bail-out?" *Journal of Financial Stability* 33: 207–223. doi:10.1016/j.jfs.2016.03.001.

Bernanke, B. S., and C. S. Lown. 1991. "The Credit Crunch." *Brookings Papers on Economic Activity* 1991 (2): 205–247. doi:10.2307/2534592.

Bhidé, A. 2010. *A Call for Judgment: Sensible Finance for A Dynamic Economy*. Oxford, New York: Oxford University Press.

[17]Although the techniques such as rapid prototyping, Toyota's Five-Whys, Intel's 'copy exactly.' and 'positive deviant' studies are systematic they do not conform to the principles of well-controlled scientific experimentation: they tolerate unexplained correlations, 'selections on the dependent variable' and ambiguous results.

Bhidé, A. 2017. "Formulaic Transparency: The Hidden Enabler of Exceptional U.S. Securitization." *Journal of Applied Corporate Finance* 29 (4): 96–111. doi:10.1111/jacf.12265.

Bhidé, A. 2019a. "Practical Knowledge: Sustaining Massively-Multiplayer Innovation." *SSRN Electronic Journal*. doi:10.2139/ssrn.3394337.

Bhidé, A. 2019b. "The Cost of Anonymous Lemons." *SSRN Electronic Journal*. doi:10.2139/ssrn.3439105.

Bhidé, A., S. Datar, and F. Villa. 2019. "Coronary Artery Bypass Grafting: Case Histories of Significant Medical Advances." *SSRN Electronic Journal*. doi:10.2139/ssrn.3427408.

Bookstaber, R. 2012. "Using Agent-Based Models for Analyzing Threats to Financial Stability." Office of Financial Research Working Paper No. 12-03. Office of Financial Research. https://www.financialresearch.gov/working-papers/2012/12/21/using-agent-based-models-for-analyzing-threats-to-financial-security/

Bookstaber, R., M. Paddrik, and B. Tivnan. 2014. "An Agent-based Model for Financial Vulnerability." Office of Financial Research Working Paper No 14-05. Office of Financial Research. https://www.financialresearch.gov/working-papers/2014/07/29/an-agent-based-model-for-financial-vulnerability/

Bookstaber, R., and M. E. Paddrik. 2015. "An Agent-Based Model for Crisis Liquidity Dynamics." Office of Financial Research Working Paper No. 15-18. Office of Financial Research. https://www.financialresearch.gov/working-papers/2015/09/16/an-agent-based-model-for-crisis-liquidity-dynamics/

Cannas, G., Ed. 2014. *Financial Activities Taxes, Bank Levies and Systemic Risk*. Luxembourg: European Union Publication Office.

Cartwright, N. 2007. *Hunting Causes and Using Them: Approaches in Philosophy and Economics*. Cambridge: Cambridge University Press.

Cetina, J., S. Rajan, and M. Paddrik. 2016. "Stressed to the Core: Counterparty Concentrations and Systemic Losses in CDS Markets." Office of Financial Research Working Paper No. 16-01. Office of Financial Research. https://www.financialresearch.gov/working-papers/2016/03/08/stressed-to-the-core/

Cherrier, B., and A. Saidi. 2019. "A Century of Economics and Engineering at Stanford." *SSRN Electronic Journal*. osf.io/tfuq7

Coase, R. H. 1937. "The Nature of the Firm." *Economica* 4 (16): 386–405. doi:10.1111/j.1468-0335.1937.tb00002.x.

De Lisa, R., S. Zedda, F. Vallascas, F. Campolongo, and M. Marchesi. 2011. "Modelling Deposit Insurance Scheme Losses in a Basel 2 Framework." *Journal of Financial Services Research* 40 (3): 123–141. doi:10.1007/s10693-010-0097-0.

Deaton, A., and N. Cartwright. 2018. "Understanding and Misunderstanding Randomized Controlled Trials." *Randomized Controlled Trials and Evidence-Based Policy: A Multidisciplinary Dialogue* 210: 2–21. doi:10.1016/j.socscimed.2017.12.005.

DiMasi, J. A., R. W. Hansen, and H. G. Grabowski. 2003. "The Price of Innovation: New Estimates of Drug Development Costs." *Journal of Health Economics* 22 (2): 151–185. doi:10.1016/S0167-6296(02)00126-1.

Dulman, S. P. 1989. "The Development of Discounted Cash Flow Techniques in U.S. Industry." *Business History Review* 63 (3): 555–587. doi:10.2307/3116040.

Fama, E. F., and M. C. Jensen. 1983. "Agency Problems and Residual Claims." *The Journal of Law & Economics* 26 (2): 327–349.

FDA (Food and Drug Administration). 1998. "Guidance for Industry: Providing Clinical Evidence of Effectiveness for Human Drugs and Biological Products." https://www.fda.gov/media/71655/download

Fisman, R., D. Paravisini, and V. Vig. 2017. "Cultural Proximity and Loan Outcomes." *American Economic Review* 107 (2): 457–492. doi:10.1257/aer.20120942.

Flood, M. D., and G. G. Korenko. 2015. "Systematic Scenario Selection: Stress Testing and the Nature of Uncertainty." *Quantitative Finance* 15 (1): 43–59. doi:10.1080/14697688.2014.926018.

Flood, M. D., and P. Monin. 2016. "Form PF and the Systemic Risk of Hedge Funds: Risk-Measurement Precision for Option Portfolios." *The Journal of Alternative Investments* 18 (4): 125–147. doi:10.3905/jai.2016.18.4.125.

Flood, M. D., P. Monin, and L. Bandyopadhyay. 2015. "Gauging Form PF: Data Tolerances in Regulatory Reporting on Hedge Fund Risk Exposures." Office of Financial Research Working Paper No. 15-13. Office of Financial Research. https://www.financialresearch.gov/working-papers/2015/07/30/gauging-form-pf/

Friedman, M. 1953. *Essays in Positive Economics*. Chicago: University of Chicago Press.

Fye, B. 2015. *Caring for the Heart: Mayo Clinic and the Rise of Specialization*. Oxford: Oxford University Press.

Galliani, C., and S. Zedda. 2015. "Will the Bail-in Break the Vicious Circle between Banks and Their Sovereign?" *Computational Economics* 45 (4): 597–614. doi:10.1007/s10614-014-9436-9.

Hands, D. W. 2001. *Reflection Without Rules: Economic Methodology And Contemporary Science Theory*. Cambridge: Cambridge University Press.

Hayek, F. 1945. "The Use of Knowledge in Society." *American Economic Review* 35 (4): 519–530.

Jones, D. S. 2000. "Visions of a Cure: Visualization, Clinical Trials, and Controversies in Cardiac Therapeutics, 1968–1998." *Isis* 91 (3): 504–541. JSTOR.

Kay, J. A., and M. A. King. forthcoming. *Radical Uncertainty: Decision-making beyond the Numbers*. 1st ed. New York: W. W. Norton & Company.

Knight, F. H. 1921. *Risk, Uncertainty, and Profit*. Boston: Houghton Mifflin.

Knudsen, T., D. A. Levinthal, and S. G. Winter. 2017. "Systematic Differences and Random Rates: Reconciling Gibrat's Law with Firm Differences." *Strategy Science* 2 (2): 111–120. doi:10.1287/stsc.2017.0031.

Kremer, M. 1993. "The O-Ring Theory of Economic Development." *The Quarterly Journal of Economics* 108 (3): 551–575. doi:10.2307/2118400.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. W. Vishny. 1998. "Law and Finance." *Journal of Political Economy* 106 (6): 1113–1155. doi:10.1086/250042.

Liu, A., M. Paddrik, S. Yang, and X. Zhang. 2016. "Interbank Contagion: An Agent-based Model Approach to Endogenously Formed Networks." Office of Financial Research Working Paper No. 16-14. Office of Financial Research. https://www.financialresearch.gov/working-papers/2016/12/20/interbank-contagion-an-agent-based-model/

Longair, M. S. 2003. *Theoretical Concepts in Physics: An Alternative View of Theoretical Reasoning in Physics*. 2nd ed. Cambridge: Cambridge University Press.

Love, J. W. 1975. "Drugs and Operations: Some Important Differences." *JAMA* 232 (1): 37. doi:10.1001/jama.1975.03250010019016.

Lucas, R. E. 1981. *Studies in Business-cycle Theory*. Cambridge: MIT Press.

Mackenzie, D. 2008. *An Engine, Not a Camera: How Financial Models Shape Markets*. Cambridge: MIT Press.

Madsbjerg, C., and M. Rasmussen. 2014. "An Anthropologist Walks into a Bar." *Harvard Business Review* 92 (3): 81–88.

Marchesi, M., M. Petracco Giudici, J. Cariboni, S. Zedda, and F. Campolongo. 2012. *Macroeconomic Cost-benefit Analysis of Basel III Minimum Capital Requirements and of Introducing Deposit Guarantee Schemes and Resolution Funds*. Luxembourg: Publications Office.

Medawar, P. B. 1982. *Pluto's Republic*. Oxford: Oxford University Press.

Mill, J. S. 1874. "On the Definition of Political Economy; and on the Method of Investigation Proper to It." In *Essays on Some Unsettled Questions of Political Economy*. http://www.econlib.org/library/Mill/mlUQP5.html

Mokyr, J. 2002. *The Gifts of Athena: Historical Origins of the Knowledge Economy*. Princeton: Princeton University Press.

Morgan, M. S. 2004. "Simulation: The Birth of a Technology to Create « Evidence » in Economics." *Revue D'histoire Des Sciences* 57: 339–375. Persée http://www.persee.fr

Munnell, A. H., ed. 1986. *Lessons from the Income Maintenance Experiments*. Boston: Federal Reserve Bank of Boston and the Brookings Institution.

Nelson, B. L. 2013. *Foundations and Methods of Stochastic Simulation: A First Course*. New York: Springer.

Nelson, R. R. 2008. "Factors Affecting the Power of Technological Paradigms." *Industrial and Corporate Change* 17 (3): 485–497. doi:10.1093/icc/dtn010.

Nelson, R. R. 2016. "The Sciences are Different and the Differences Matter." *Research Policy* 45 (9): 1692–1701. doi:10.1016/j.respol.2015.05.014.

Nelson, R. R., and S. G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge: Belknap Press of Harvard University Press.

Nightingale, P. 2004. "Technological Capabilities, Invisible Infrastructure and the Un-social Construction of Predictability: The Overlooked Fixed Costs of Useful Research." *Research Policy* 33 (9): 1259–1284. doi:10.1016/j.respol.2004.08.008.

Paddrik, M., H. Anderson, and J. J. Wang. 2016a. "Bank Networks and Systemic Risk: Evidence from the National Banking Acts." Office of Financial Research Working Paper, No. 16-13. Office of Financial Research. https://www.financialresearch.gov/working-papers/2016/12/06/bank-networks-and-systemic-risk/

Paddrik, M., R. Hayes, W. Scherer, and P. Beling. 2014. "Effects of Limit Order Book Information Level on Market Stability Metrics." Office of Financial Research Working Paper No. 14-09. Office of Financial Research: https://www.financialresearch.gov/working-papers/2014/11/25/effects-of-limit-order-book-information-level-on-market-stability-metrics/

Paddrik, M. E., and P. Young. 2017. "How Safe are Central Counterparties in Derivatives Markets?" Office of Financial Research Working Paper No. 17-06. Office of Financial Research. https://www.financialresearch.gov/working-papers/2017/11/02/how-safe-are-ccps/

Paddrik, M. E., S. Rajan, and P. Young. 2016b. "Contagion in the CDS Market." Office of Financial Research Working Paper No. 16-12. Office of Financial Research. https://www.financialresearch.gov/working-papers/2016/12/01/contagion-in-the-cds-market/

Pritchett, L. forthcoming. "Randomizing Development: Method or Madness?." In *Randomized Control Trials in the Field of Development: A Critical Perspective*, edited by F. Bédécarrats, I. Guérin, and F. Roubaud. Oxford: Oxford University Press.

Roth, A. E. 2002. "The Economist as Engineer: Game Theory, Experimentation, and Computation as Tools for Design Economics." *Econometrica* 70 (4): 1341–1378. doi:10.1111/1468-0262.00335.

Sahlman, W. A. 1990. "A Cautionary Tale about Discounted Cash Flow Analysis." Harvard Business School Division of Research Working Paper No. 90-069.

Shapin, S. 1996. *The Scientific Revolution*. Chicago: University of Chicago Press.

The Nobel Prize. 2019a. "Herbert A. Simon - Biographical." https://www.nobelprize.org/prizes/economic-sciences/1978/simon/biographical/

The Nobel Prize. 2019b. "Advanced Information." https://www.nobelprize.org/prizes/economic-sciences/2019/advanced-information/

University of Alabama at Birmingham. 2016. "Zebrafish's Growing Impact on Medical Research." *ScienceDaily*, July 19. Accessed November 22 2017. www.sciencedaily.com/releases/2016/07/160719161816.htm

Vincenti, W. G. 1990. *What Engineers Know and How They Know It: Analytical Studies from Aeronautical History*. Baltimore: Johns Hopkins University Press.

Appendices

Appendix 1. Details of Simulation Model

Assumptions about loans and creditworthiness:

All loans are for identical amounts and are extended for a single time period. Interest accrues becomes due, along with the principal, at the end of the period.

All applicants believe they are creditworthy and therefore eligible for loans at 'prime' interest rates. However only some proportion (denoted by the variable *GoodProportion*) are actually capable of and willing to fully repay their loan obligations.

All other borrowers default, imposing identical losses on lenders. We denote this loss (which includes unpaid principal and accrued interest) by the variable *Loss*, expressed as a percentage of the loan amount.

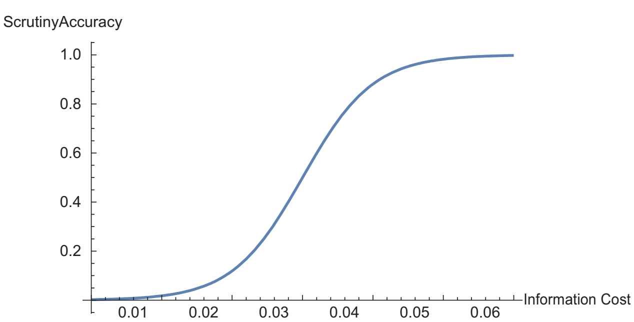
Prime Offers Made

Lenders offer 'prime' loans to applicants they have categorized as creditworthy ('good'). The accuracy of the categorization increases with the *InfoCost* (expressed as a proportion of the loans applied for) that lenders incur to secure information about applicants and the efficiency of such expenditures (denoted by *InfoEfficiency*).

In particular I specify *ScrutinyAccuracy* using the following modified logit function:

$$Scrutiny\ Accuracy = \frac{1}{e^{-(InfoCost*InfoEfficiency-6)}+1}$$

To illustrate: setting *InfoEfficiency* = 200 provides the following plot of the accuracy of categorization as a function of the information costs incurred by lenders.



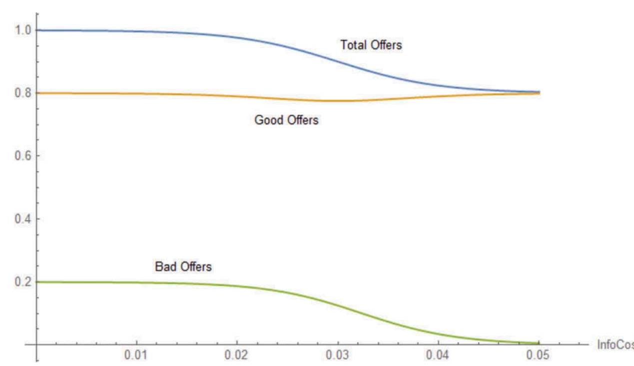
My model further stipulates that:

- The proportion of applications rejected by lenders – denoted by *PrimeRejections* and expressed as proportion of total applications – equals *ScrutinyAccuracy *(1-Goodproportion)*.
- Incorrect rejections of good applications – denoted by *FalPosProportion* and expressed as proportion of all rejections – equals *(1-ScrutinyAccuracy)/2*. Thus, when *ScrutinyAccuracy* = 0, half the rejections are 'false positives' and when *ScrutinyAccuracy* = 1 there are no false positives.[18]

This gives us:

- *PrimeOffersTotal* = *1* – *PrimeRejections* (= prime loans offered, expressed as a proportion of total applicants)
- *PrimeOffersGood* = *Goodproportion* – *FalPosProportion* PrimeRejections* (= prime loans offered to good applicants, expressed as a proportion of total applicants)
- *PrimeOffersBad* = *PrimeOffersTotal* – *PrimeOffersGood* (= prime loans offered to bad applicants, expressed as a proportion of total applicants).

To illustrate, if as before we set *InfoEfficiency* = 200 and *GoodProportion* = 80% we get the following plot of how total,



good and bad offers (expressed as a proportion of total applications) vary with the lender's information expenditures.

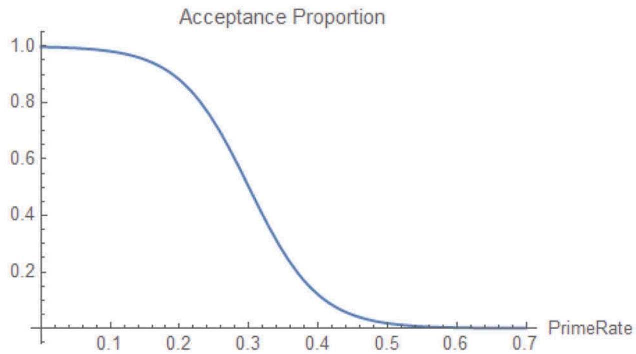
Prime Offers Accepted

The proportion of applicants accepting loan offers (denoted by *AcceptanceProportion*) decreases with the interest rate on the offers (denoted by the *PrimeRate*) and a *RateSensitivity* parameter as specified by the following modified logistic function.

$$AcceptanceProportion = \frac{1}{e^{-(PrimeRate*RateSensitivity-6)}+1}$$

To illustrate: setting *GoodProportion* = 0.8 and *RateSensitivity* = 20 provides the following plot of the acceptance of prime loan offers as a function of interest rates.

[18]This assumption entails a minor discontinuity: *FalPosProportion* jumps from zero when *InfoCost* = 0 (because no applications are rejected) to ½ when *InfoCost* is negligible but not zero. The discontinuity does not however lead to any large jump in false positives expressed as a proportion of applications which, at low *InfoCost*, are much larger than the number of rejections.



AcceptanceProportion in turn lets us compute:

- *PrimeAcceptancesGood* = *AcceptanceProportion* PrimeOffersGood* (= prime loan offers accepted by good borrowers expressed as a proportion of total loan applications)
- *PrimeAcceptancesBad* = *AcceptanceProportion* PrimeOffersBad* (= prime loan offers accepted by bad borrowers expressed as a proportion of total loan applications)
- *PrimeAcceptancesTotal* = *PrimeOffersGood* + *PrimeOffersBad* (= total prime loans accepted expressed as a proportion of total loan applications)

Profits from prime lending

Lenders' profits equal interest earnings minus loans losses and costs:

- *Interest earnings*, which accrue but are only realized when good borrowers repay their loans, equal *PrimeRate*PrimeAcceptancesGood*
- *Losses* incurred on loans bad borrowers (which include unpaid principal and accrued interest) equal *Loss*PrimeAcceptancesBad*
- *Costs*. Lenders fund loans with insured deposits that depositors consider risk free and therefore do not demand a 'real' interest rate. But although the 'direct' real cost for funding loans is zero, lenders do incur an implicit cost of maintaining a capital cushion that equals

CapitalCost * (*PrimeAcceptancesGood* + *PrimeAcceptancesBad*).

And as mentioned, lenders also incur *InfoCost*s on all applications received.

Accordingly, π*Prime*, the net profit on prime loans (expressed as a proportion of total loan applications) is given by

$\pi Prime = (PrimeRate - CapitalCost)* PrimeAcceptancesGood - (Loss + CapitalCost)* PrimeAcceptancesBad - InfoCost.$

And because *PrimeAcceptancesGood* and *Prime AcceptancesBad* can be expressed as a function of the five 'structure' variables, namely *GoodProportion, CapitalCost, Loss, RateSensitivity and InfoEfficiency*, π*Prime* too can be expressed as a function of the five 'structure' variables and the two 'choice' variables, *PrimeRate* and *InfoCost*.

Choosing *PrimeRate* and *InfoCost*

In principle, we should be able to compute a *BreakEvenPrimeRate* – the lender's choice of *PrimeRate* in markets where competition forces lending at 'no-profit/no-loss' rates – by solving for $\pi Prime = 0$. Similarly, we should be able to compute a π*MaxPrimeRate* for markets where lenders can set rates to maximize profits by solving for $\frac{\partial \pi \mathrm{Prime}}{\partial \mathrm{PrimeRate}} = 0$.

But the complexity of the π*Prime* function precludes analytical or numerical solutions; however, if the values of the five 'structure' variables are fixed, the software can produce plots of the *BreakEvenPrimeRate* and the π*MaxPrimeRate* as a function of *InfoCost*. (Figure 1).

Similarly, and even after fixing the five structure variables, we cannot compute the profit maximizing *InfoCost* by solving for $\frac{\partial \pi \mathrm{MaxPrime}}{\partial \mathrm{InfoCost}} = 0$. But the model can produce plots (Figure 2) of 'performance' variables (such as good and bad loans made) as a function of *InfoCost* when lenders charge break-even and profit maximizing rates.

Non-prime lending

Lenders offer 'non-prime' loans to all applicants they have rejected for prime loans without incurring any further information costs.

The loans are offered at a *NonPrimeRate* that reflects the higher expected defaults by the rejected applicant but only to break-even rather than to make a profit. I further assume that the *RateSensitivity* of applicants offered non-prime loans is 1/25th of the rate sensitivity applicants offered prime loans. Otherwise there would be virtually no non-prime loan acceptances at rates which allow lenders to at avoid losses.

Then, following the previous terminology and sequence, we get:

$NonPrimeOffersTotal = PrimeRejections$

$NonPrimeOffersGood = GoodPrimeRejected$

$NonPrimeOffersBad = NonPrimeOffersTotal - NonPrimeOffersGood$

$NonPrimeAcceptanceProportion = \frac{1}{e^{-(PrimeRate*(RateSensitivity/25)-6)}+1}$

$NonPrimeAcceptancesGood = NonPrimeAcceptanceProportion * NonPrimeOffersGood$

$NonPrimeAcceptancesBad = NonPrimeAcceptanceProportion * NonPrimeOffersBad$

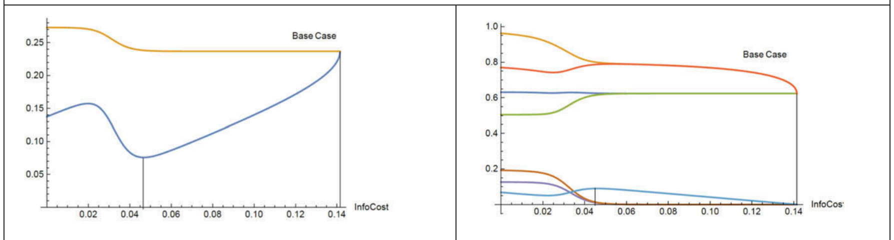
$\pi NonPrime = (NonPrimeRate\text{-}CapitalCost) * NonPrimeAcceptancesGood - (Loss+CapitalCost) * NonPrimeAcceptancesBad$

Finally, as with prime loans, the breakeven non-prime lending rate is plotted against the *InfoCost* (incurred to make the prime loans) by solving for the rate at which $\pi NonPrime = 0$ – after fixing the values of the five structure variables. This gives us Figure 3 in the main text.

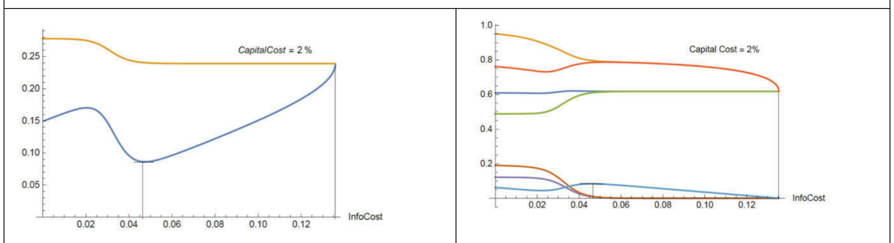
Appendix 2. How Structure Can Affect Lending Performance

The plots below depict the results of varying the ‘structure’ variables from the base case presented in Section 5 of the main text.

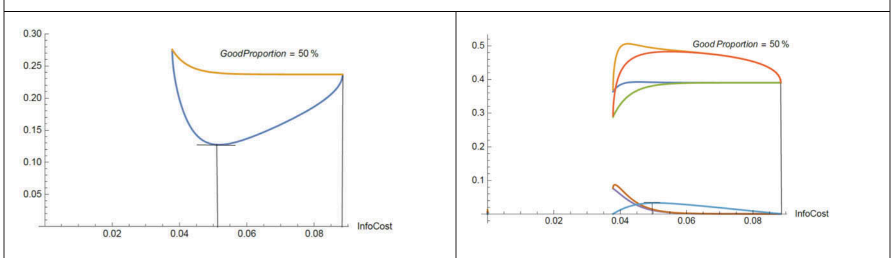
Base Case Plots (repeated without legends from Figures 1 and 2)



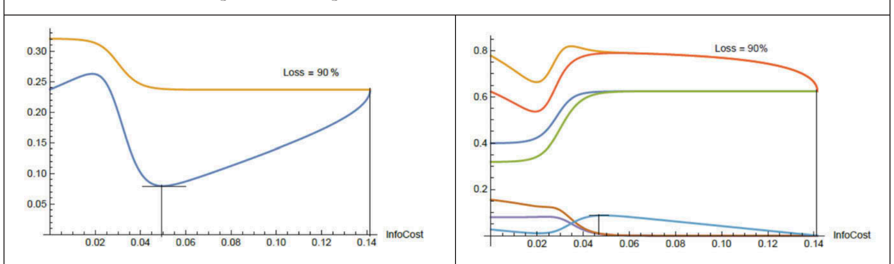
2 X Base-Case *CapitalCosts* (legends as in Figures 1 and 2)



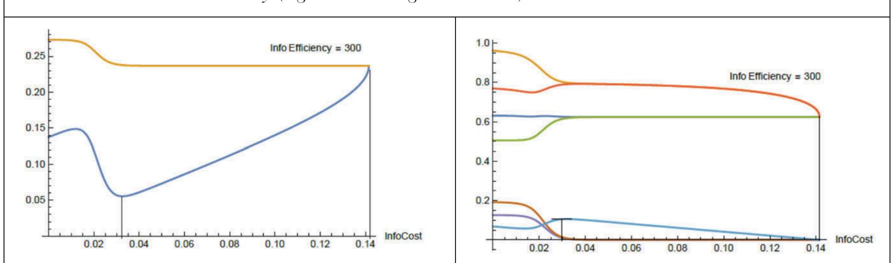
0.5 X Base-Case *GoodProportion* (legends as in Figures 1 and 2)



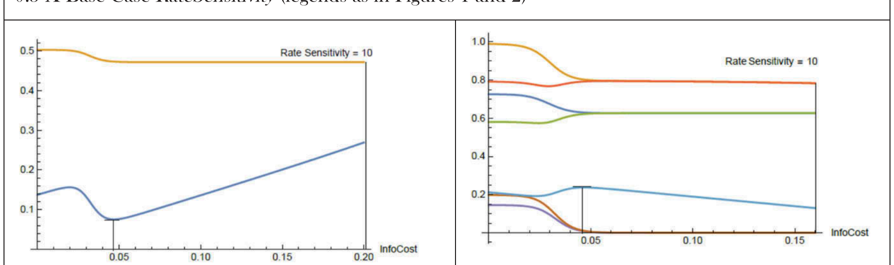
1.8 X Base-Case *Loss* (legends as in Figures 1 and 2)



1.5 X Base-Case *InfoEfficiency* (legends as in Figures 1 and 2)



0.5 X Base-Case *RateSensitivity* (legends as in Figures 1 and 2)



The plots whose highlights are summarized in Table 3, suggest that:

- Doubling capital costs (from the base case) does not materially increase interest rates or reduce loan volumes. Increased capital costs have a more significant effect on lenders' profits, especially under rules which require 'overspending' on information.
- An 80% increase in the *Lgoss* variable from the base-case has a much more significant impact than a 100% increase in capital costs under 'US- style' information restricting rules. Expectedly, the effects of the increased *Loss* declines when the rules allow or require lenders to spend more on information (because at high levels of *InfoCosts* losses disappear).
- Halving the proportion of good applicants from the base case makes it impossible for lenders to avoid losses when *InfoCosts* are less than 3.8% or greater than 8.8%.
- A 50% improvement in the *InfoEfficiency* parameter from the base-case increases lenders' profits more than it does loans made.
- A 50% reduction in the borrower's *RateSensitivity* parameter significantly increases interest rates and lenders' profits in monopolistic markets; in competitive markets, rates also increase, but not to the same degree.

Table 3.

	Base case	CapitalCost = 2X base	Loss = 1.8 X base	GoodProportion = 0.5X base	Info Efficiency = 1.5 X base	Rate Sensitivity = 0.5X base
Zero Information Cost ('US' rules)						
Highly competiive markets (break-even rates)						
Interest Rate (%)	14	15	24	No lending possible without lenders incurring losses	14	14
Loans made/Applications submitted (%)	96	95	77		96	99
Monopolistic Markets (profit maximized rates)						
Interest Rate (%)	27	28	32		27	50
Loans made/Applications submitted (%)	62	61	40		62	72
Profit Earned by lenders (%)	6.8	6.4	2.7		6.8	21
Lowest information Cost that eliminates bad loans						
InformationCost (% of loan applied for)	5.7	5.7	6.1	6.2	4.8	5.7
Highly competiive markets (break-even rates)						
Interest Rate (%)	8.2	9.3	8.8	14	7.1	8.2
Good Loans/Good Applications (%)	99	99	98	96	99	99
Monopolistic Markets (profit maximized rates)						
Interest Rate (%)	24	24	24	24	24	47.2
Good Loans/Good Applications (%)	79	77	77	78	77	78
Profit Earned by lenders (%)	8.9	7.3	6.7	2.3	9.7	23
2X Lowest Information Cost ('European' rules)						
InformationCost (% of loan applied for)	11.4	11.4	12.2	No lending possible without lenders incurring losses	9.6	11.4
Highly competiive markets (break-even rates)						
Interest Rate (%)	16	17	18		13	16
Total Loans/Applications (%)	75	74	73		77	79
Good Loans/Good Applications (%)	94	92.1	92		96	99
Monopolistic Markets (profit maximized rates)						
Interest Rate (%)	24	24	24		24	47
Total Loans/Applications (%)	62	62	62		62	62
Good Loans/Good Applications (%)	78	77	78		78	78
Profit Earned by lenders (%)	2.7	1.9	2		4.4	17.4