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Disproportionate Safety Preference and the Innovation of Fintech Shadow Banking

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Abstract

There has been a dramatic shift in financial intermediation in the last 10 - 15 years from traditional banks to shadow banks (non-depository institutions that rely on originate-to-distribute lending model). We link this rise to an emerging literature that shows that certain and uncertain utility functions are different with a disproportionate preference for certainty. We show that such a preference plays a role in diverting lending away from the traditional banking model to the shadow banking model. Furthermore, a low interest-rate environment emerges as the key contributing factor in the dramatic rise of shadow banking.

Keywords

Fintech Shadow Banks, Certain Utility, Uncertain Utility, Securitization

1. Introduction

To explain the key paradoxical departures from expected utility theory (Allais paradoxes), Allais (1953) notes that people "greatly value certainty". Apart from motivating a general re-thinking of behavior under risk, more recently this observation has inspired literature that shows that certain and uncertain utility functions are different with a disproportionate preference for certainty[1] (see Serfilippi et al. (2019), Andreoni and Sprenger (2012, 2010), Simonsohn (2009), and Gneezy et al. (2006)). In this article, we show that such a preference may be behind the phenomenal rise of Fintech shadow banks over the past 10 - 15 years[2]. Fintech shadow banks are non-depository institutions that rely on technology and data analytics as being central to their business model[3]. They do not keep

[1]Siddiqi (2017) applies this perspective to the financial innovation of securitization.
[2]See Buchak et al. (2018) for empirical evidence of this rise.
[3]See BIS annual report 2019, chapter III.

loans on their balance-sheets. Rather, they utilize an originate-to-distribute model where loans are pooled together and ultimately sold to investors as bonds. This is in sharp contrast with the traditional banking model of originate-to-keep where loans are kept on the balance-sheet as income generating assets.

A disproportionate preference for certainty (DPC) increases the present-value of future cashflows if they are split into certain and uncertain components. As the originate-to-distribute model of shadow banking accomplishes this split (via securitization), it taps into this additional value, which is higher in a low interest-rate environment.

This paper is organized as follows. Section 1 shows how the present value of cashflows is different under "disproportionate safety preference". Section 2 discusses the impact of "disproportionate safety preference" on financial intermediation and derives the key results. Section 3 discusses the unintended policy consequences of ignoring shadow banks. Section 4 concludes with recommendations for further research.

2. The Present Value under a Disproportionate Preference for Certainty

We assume that investors maximize expected utility of consumption over two points in time, time-0 and time-1 as follows:

$$u(c_0)+\beta E\left[u(c_1)\right]$$

where c_0 and c_1 are time-0 and time-1 consumption respectively, and $\beta<1$ is the time-discount factor.

$$c_0 = w_0 - \sum_i^N P_i n_i$$

$$c_1 = \sum_i^N X_i n_i$$

where w_0 is time-0 wealth, P_i is the price of asset *i* at time-0, n_i is the number of shares of asset *i* bought, and X_i is the time-1 payoff from asset *i*.

Broadly consistent with the literature on DPC (Nielson, 1992; Schmidt, 1998; Diecidue et al., 2004) and as defined in Andreoni and Sprenger (2010), we take the simplest approach and assume that certain outcomes are evaluated with a utility function, $u^S(c)$, which is $1+\alpha$ times the utility function, $u^R(c)$, used to evaluate uncertain outcomes:

$$u^S(c)=(1+\alpha)u^R(c) \tag{1.1}$$

where $\alpha>0$ is a constant.

P_i which is equal to the present value of expected cashflows, $PV\left[E(X_i)\right]$, is obtained as follows:

$$P_i u'^S(c_0)=\beta E\left(u'^R(c_1)X_i\right)$$

where the known price today is evaluated with the certain utility function,

$u^S(c)$, and the risky payoff at time-1 is evaluated with the uncertain utility function, $u^R(c)$.

It follows that:

$$P_i = PV\left[E(X_i)\right] = \frac{\beta E\left(u'^R(c_1)X_i\right)}{(1+\alpha)u'^R(c_0)} \tag{1.2}$$

Noting that $\frac{\beta u'^R(c_1)}{u'^R(c_0)}$ is the stochastic-discount-factor (*SDF*), (1.2) can be re-written as:

$$PV\left[E(X_i)\right] = \frac{E(SDF \cdot X_i)}{1+\alpha} \tag{1.3}$$

$$\Rightarrow PV\left[E(X_i)\right] = \frac{1}{1+\alpha}\left[E(SDF)E(X_i) + Cov(X_i, SDF)\right] \tag{1.4}$$

(1.4) provides the present value of risky payoff under DPC which is lower than the present value under the standard expected utility approach:

$$PV\left[E(X_i)\right] = \left[E(SDF)E(X_i) + Cov(X_i, SDF)\right] \tag{1.4a}$$

The present value of risk-free payoff, X_F, under DPC is the same as with the standard expected utility approach:

$$PV\left[X_F\right] = E(SDF)X_F \tag{1.4b}$$

3. Financial Intermediation under a Disproportionate Preference for Certainty

Buchak et al. (2018) define shadow banks as non-depository institutions that fall outside the scope of traditional banking regulation and Fintech shadow banks as non-depository institutions that heavily leverage technology to provide services to customers. See Buchak et al. (2018) for detailed empirical evidence on the phenomenal rise of shadow banking and Fintech shadow banking over the last decade and a half.

Consider a financial intermediary choosing between two different types of banking models, the traditional originate-to-keep model versus the Fintech originate-to-distribute model. Assume that the project under consideration requires a loan of I_0. The intermediary charges an interest rate, r_B, which is assumed to be exogenously fixed for simplicity. The loan is contracted at time-0 and falls due at time-1. If the project succeeds, which has an exogenous probability of π, then the project returns a payoff of $I_1 = I_0(1+r_B)$ to the lender. If the project fails, then the lender only gets a fraction, *f*, of funds back where $f < 1$. That is, $I_1 = fI_0$ if the project fails which has a probability of $1-\pi$.

The intermediary chooses between the two funding models based on the net present value (*NPV*) criterion. Under the traditional originate-to-keep model, there are compliance costs associated with keeping the loan on the balance sheet. These compliance costs arise from various regulatory measures such as maintaining a minimum capital ratio and depend on the loan amount. We express these compliance costs as a percentage, δ_B, of the loan amount I_0.

$$NPV(\text{Originate to Keep}) = PV\left[E(I_1)\right] - I_0(1+\delta_B) \tag{2.1}$$

The intermediary may choose the originate-to-distribute model where the loan is split into certain and uncertain components and ultimately sold to investors. This is accomplished via securitization (Siddiqi, 2017). However, the securitization process is costly. We express the associated costs, as a percentage, δ_S, of the loan amount. We make the realistic assumption that $\delta_S > \delta_B$. The safe cashflow that can be carved-out from the loan of I_0 is fI_0 as that is the cashflow that the lender gets if the project fails. So, NPV under the originate-to-distribute model is:

$$NPV(\text{Originate to Distribute}) = PV\left[E(I_1 - fI_0)\right] + PV\left[fI_0\right] - I_0(1+\delta_S) \tag{2.2}$$

If the NPV in (2.2) is higher than the NPV in (2.1) (if both are positive), then the intermediary uses the originate-to-distribute model. If the NPV in (2.1) is higher, than the intermediary uses the originate-to-keep model.

The decision to switch from originate-to-keep model to originate-to-distribute model is based on a comparison of additional benefits versus additional costs of switching. The additional cost of switching is:

$$I_0(\delta_S - \delta_B) \tag{2.3}$$

To measure the additional benefit of switching, use (1.4) and (1.4b) to obtain:

$$\begin{aligned} &PV\left[E(I_1 - fI_0)\right] + PV\left[fI_0\right] \\ &= \frac{1}{(1+\alpha)}\left[E(SDF)E(I_1 - fI_0) + Cov(I_1, SDF)\right] + E(SDF)fI_0 \end{aligned} \tag{2.4}$$

$$PV\left[E(I_1)\right] = \frac{1}{(1+\alpha)}\left[E(SDF)E(I_1) + Cov(I_1, SDF)\right] \tag{2.5}$$

Subtract (2.5) from (2.4) to obtain the additional benefit from switching:

$$\frac{\alpha}{1+\alpha}\left(\frac{fI_0}{R_F}\right) \tag{2.6}$$

where $R_F = \dfrac{1}{E(SDF)}$ is the (gross) risk-free rate.

Proposition 1 (Originate-to-Distribute vs Originate-to-Keep) ***A financial intermediary switches to the originate-to-distribute model if the following condition holds*:**

$$\frac{\alpha}{1+\alpha}\left(\frac{fI_0}{R_F}\right) > I_0(\delta_S - \delta_B) \tag{2.7}$$

Proof

$\dfrac{\alpha}{1+\alpha}\left(\dfrac{fI_0}{R_F}\right)$ in (2.7) is the marginal benefit from switching and $I_0(\delta_S - \delta_B)$

is the marginal cost. It follows that a financial intermediary will switch to the originate-to-distribute model if marginal benefit of doing so exceeds the marginal cost. ■

Proposition 1 simply states that if the additional benefit of switching to originate-to-distribute model exceeds the costs of doing so, then a financial intermediary makes the switch.

Several additional insights follow from (2.7). It is straightforward to see that higher the size of safe cashflows, fI_0, bigger is the benefit from switching. So, one expects to see the originate-to-distribute model more in sectors where a bigger fraction of safe cashflows is found. For example, in the residential mortgage market. Unsurprisingly, this is where the originate-to-distribute model is most popular (Buchak et al., 2018).

It follows directly from (2.7) that a low interest rate environment is especially conducive for the originate-to-distribute model.

Proposition 2 ***A low risk-free rate increases the additional benefit from switching to the originate-to-distribute model.***

Proof

If the risk-free rate, R_F, falls in (2.7), then the additional benefit of switching to originate-to-distribute model rises. That is, $\frac{\alpha}{1+\alpha}\left(\frac{fI_0}{R_F}\right)$ rises in (2.7) as R_F falls. ■

Furthermore, as can be directly seen from (2.7), increasing the regulatory requirements on the traditional banking sector, which has the effect of pushing up the compliance cost, δ_B, increases the incentive to switch to the originate-to-distribute model.

Proposition 3 ***Increasing the regulatory burden associated with the traditional banking model increases the incentive to switch to the originate-to-distribute model.***

Proof

Defining the difference between additional benefit and additional cost as:

$$v = \frac{\alpha}{1+\alpha}\left(\frac{fI_0}{R_F}\right) - I_0\left(\delta_S - \delta_B\right) \tag{2.8}$$

$$\frac{\partial v}{\partial \delta_B} = I_0 > 0$$

Hence, v rises as δ_B rises. It follows that the incentive to switch is stronger, higher the value of δ_B, all else equal. ■

As the above results show, after the global financial crisis of 2008, a combination of factors has come into play that created key advantages for the originate-to-distribute model. Firstly, quantitative easing resulting in a decline in interest rates across the yield curve has increased the additional benefit offered by the originate-to-distribute model. Secondly, increased regulatory burden on the traditional originate-to-keep model has made the incentive to shift stronger. Given these results, it makes sense that the Fintech originate-to-distribute model has seen such a remarkable growth post GFC-2008.

4. The Unintended Consequences of Policy

While evaluating the impact of policy interventions, policy makers need to be mindful of the shadow banking sector as well. If the shadow banking sector is ignored, then the impact of policy interventions can either be underestimated or overestimated. For example, regulatory changes that are designed to tighten bank lending (such as higher capital ratio requirement) could cause lending to migrate from the traditional originate-to-keep model to the new originate-to-distribute model typical of the Fintech shadow banks. So, there could be a decline in risky bank lending in the traditional sector without any overall decline in such lending when shadow banks are also taken into account. Hence, ignoring the shadow banking sector amounts to overestimating the success of policy in mitigating risky lending. Another example is QE monetary easing which lowers interest rates. The benefit of low interest rates is underestimated if only the traditional banking sector is considered as low interest rates are especially beneficial to the shadow banking sector causing lending to migrate to that sector.

5. Conclusion

The rise of the Fintech shadow banking sector in the past 10 - 15 years has been phenomenal. The defining feature of this sector has been the splitting of safe and risky payoffs via securitization, which are then sold to investors as bonds. This is in sharp contrast with the traditional banking model where loans are kept on the balance sheet as income generating assets. In this article, we connect the rise of Fintech shadow banking to recent literature on certain and uncertain utility inspired by an early observation of Allais (Allais paradox). We show that a disproportionate preference for certainty or DPC as modelled in the literature provides a natural explanation for the phenomenal rise of Fintech shadow banks. Policy makers run the risk of either underestimating or overestimating the impact of a policy intervention if they do not also take into account the impact of the intervention on the shadow banking sector. Overall, disproportionate safety preference provides a new way of understanding the rise of shadow banks. Empirically evaluating the power of this explanation is a natural subject for future research.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'ecole americaine. *Econometrica, 21,* 503-546. https://doi.org/10.2307/1907921

Andreoni, J., & Sprenger, C. (2010). *Certain and Uncertain Utility: The Allais Paradox and Five Decision Theory Phenomena*. Levine's Working Paper Archive.

Andreoni, J., & Sprenger, C. (2012). Risk Preferences Are Not Time Preferences. *American Economic Review, 102,* 3357-3376. https://doi.org/10.1257/aer.102.7.3357

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. *Journal of Financial Economics, 130,* 453-483. https://doi.org/10.1016/j.jfineco.2018.03.011

Diecidue, E., Schmidt, U., & Wakker, P. P. (2004). The Utility of Gambling Reconsidered. *Journal of Risk and Uncertainty, 29,* 241-259. https://doi.org/10.1023/B:RISK.0000046145.25793.37

Gneezy, U., List, J. A., & Wu, G. (2006). The Uncertainty Effect: When a Risky Prospect Is Valued Less Than Its Worst Possible Outcome. *The Quarterly Journal of Economics, 121,* 1283-1309. https://doi.org/10.1093/qje/121.4.1283

Nielson, W. S. (1992). Some Mixed Results on the Boundary Effect. *Economics Letters, 39,* 275-278. https://doi.org/10.1016/0165-1765(92)90260-6

Schmidt, U. (1998). A Measurement of the Certainty Effect. *Journal of Mathematical Psychology, 42,* 32-47. https://doi.org/10.1006/jmps.1997.1197

Serfilippi, E., Carter, M., & Guirkinger, C. (2019). Insurance Contracts When Individuals "Greatly Value" Certainty: Results from a Field Experiment in Burkina Faso. *Journal of Economic Behavior and Organization, 180,* 731-743. https://doi.org/10.1016/j.jebo.2019.07.017

Siddiqi, H. (2017). Certain and Uncertain Utility: A New Perspective on Financial Innovation. *Economics Letters, 158,* 7-9. https://doi.org/10.1016/j.econlet.2017.06.009

Simonsohn, U. (2009). Direct Risk Aversion: Evidence from Risky Prospects Valued Below Their Worst Outcome. *Psychological Science, 20,* 686-692. https://doi.org/10.1111/j.1467-9280.2009.02349.x