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Predatory cells and puzzling financial crises: Are toxic products good for the financial markets?

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ABSTRACT

We advance the idea that the predator-prey dynamics that take place among key market agents play an important role in explaining financial crises. As such, we posit that financial markets evolve through fault lines involving toxic behaviors (such as deceit), toxic products (such as predatory mortgages) and inefficient regulations. We provide data to show that the puzzle of the lack of congruence between the market behaviors and what some economic models predict at times of financial crises may be the result of predator-prey interplays, and of so-called "predatory cells", which are under the influence of financial accelerators.

1. Introduction[1]

While there have been many theories presented in an attempt to explain financial crises (e.g., Abreu and Brunnermeier, 2003), few to our knowledge have argued that these can in the end be beneficial for the financial markets and the economy, despite the fact that they have caused harm at some point in the process (Akerlof and Shiller, 2015). Many economic models fall short of explaining how markets eventually become dysfunctional (Colander et al., 2009). More systematic study of financial crises with an eye to understanding the role of predatory behaviors has been far less common, although some discussions have taken place on the subject (Conlisk, 2001).

Certainly, some convincing explanations have been presented with respect to biases (Kahneman and Tversky, 1979) and overconfidence (Scheinkman and Xiong, 2003), including with respect to key lenders such as large banks[2] (Ho et al., 2016). Other authors have examined the contractual and opportunistic nature of business relationships (Williamson, 1981), systemic risk (Hellwig, 2009) and the tendency to market so-called "lemons" or toxic products (Akerlof, 1970). Looking at market agents' reactions from an ethical point of view (Ericson and Doyle, 2003; Neal and Wheatley, 1998; Akerlof and Shiller, 2009) or at the psychological profile of these actors (Christie and Geis, 1970; Boddy, 2011; Scherbina, 2013), has not explained the gap between the real and predicted levels of risk aversion. The same observation applies when considering structural problems (Allen and Gale, 1999; Abreu and Brunnermeier, 2003; Iacoviello, 2008; Hellwig, 2009; Rajan, 2010; Graafland and van de Ven, 2011; Roy and Kemme, 2012; Jizi et al., 2014) as well as shortcomings at the level of policy-making (Friedman and Schwartz, 1963; Stiglitz, 2003; Sama and Shoaf, 2005; Taylor, 2009; Krugman, 2009).

Economists have been searching for the root causes of crises. Yet, forecasting the latter has been a challenge, in part due to lack of research funding and connection with the psychological aspects of agents' behaviors (Colander et al., 2009). Overall, the press and academicians acknowledge the existence of toxic behaviors. However, few of these authors maintain that toxic behaviors can actually result in improving financial markets once crises are resolved, and that is the position we take in the present paper. We show that the puzzle of the unexplained gap

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[1] We wish to thank for their for their sound advice and precious recommendations the following professors: Paresh Narayan, Editor, Economic Modelling and the reviewers, as well as Alain Charbonneau (UQO).

[2] Overconfidence, especially among lenders such as banks, renders them vulnerable (Ho et al., 2016).

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between the market agents' behaviors and what many economic models predict can be explained from a predator-prey perspective, at least in part[3,4]. The context of bad and excessive decisions as well as irrational reactions (De Bondt and Thaler, 1985) includes the timing of the transaction (Shefrin and Statman, 1985), the presence of markets that are filled with toxic products (Odean, 1998), and the presence of asymmetric information between the market agents (Goodhart, 1999).

The fact that investors act irrationally (e.g., Shiller, 2005), inconsistently (Smith et al., 1988), pathologically (Kamihigashi, 2008), or else adopt predator-like behaviors (Carney et al., 2010) has been discussed by scholars. Their views contrast with the theory of the homo-economicus (Cohen, 2012), who is supposed to be rational at all times and to seek welfare utility maximization rather than immediate financial gains. We contend that when investors engage in greedy investments and panic behaviors, as seen during the US 2007–2009 predatory-mortgages crisis, they actually follow some form of rationality. They ultimately do aim for their well-being, not realizing, however, that they are immersed in a 'badfare' economy in the meantime. The analyses we provide in this paper show that even irrational and mere profit-seeking behaviors can be explained and are part of a market's overall logic that pushes for its historical betterment. In other words, market agents can be temporarily sidetracked or overwhelmed by markets that rely on "Bads" (bad products paired with toxic information), but eventually they tend to try to reach a new equilibrium that secures their zone of economic and financial comfort.

Our contribution to the literature is to show that the US financial market that we examined contains a constant (k), which measures the ratio of predator to prey behavior[5] (see Appendix 1). Along this line, we discuss the normal distribution curves associated with the three moments said to characterize a financial crisis (herding, swarming and stampeding – see Appendix 1). We show that they are in fact the result of slightly modified Lotka-Volterra equations (Lotka, 1920, 1925; Volterra, 1926, 1931),[6] with a modification that includes this k constant. They in turn can be approximated by a sinusoidal function. This k constant is important because it rests on the assumption that markets are bounded (Simon, 1957), and more to the point, rationally bounded. Markets are closed dynamic systems, an observation that outlines the fact that whatever exuberant behavior that market agents adopt (Shiller, 2005), a new dynamic equilibrium will eventually be reached with cooperation or aggression made possible between sellers and buyers.

More particularly, we show that the puzzle of the difference between the actual market behavior with respect to risk aversion and what some economic models predict can be re-examined by including predator-prey dynamics.

This article is organized as follows. The first section of this paper reviews the literature with respect to models of financial crises. The second section discusses our findings. Next, we show that the market history, in the US at least, can be explained by modified Lotka-Volterra equations[7] that can be approximated by a sinusoidal function. In the fourth section, we isolate some US-based financial crisis episodes. We conclude by revisiting the main assumptions of the psychological Consolidated Model of Financial Predation (CMFP.

2. The puzzle of questionable decisions by key market agents amplifying financial crises

Economic models that assume that competitive markets are without friction justifiably recognize that asset prices are the result of the interplay between the forces of aggregate supply and aggregate demand. Assets include, of course, tradable items such as bonds and equities, and less liquid assets such as real estate, buildings and equipment, patents, and so forth. It is also assumed that there is no feedback, or else that feedback is kept to a minimum. The Arrow-Debreu model (Arrow and Debreu, 1954) offers a perfect worldview whereby contingent claims insure market agents against any events, thus easing their choices (see also Geanakoplos, 2008). By contrast, other models discuss feedback mechanisms, frictions, imperfections, and financial accelerators (Claessens and Kose, 2017b). The Gordon model (Gordon, 1959, 1962)[8] clarifies the determination of equity prices. Generally, the price of an asset that offers a perpetual stream of dividends takes into account the discount rate and the nominal growth rate of the dividends. Decisions are overall relatively simple: they rely on current data, some expectations about the future, as well as parameters that minimize the impact of market frictions and feedback. The CAPM model (Sharpe, 1964; Lintner, 1965; Mossin, 1966) is a good representation of an assessment of the market's rate of return in the context of a partial equilibrium assumption.[9]

According to these approaches, it appears unlikely that a market would behave irrationally. Market agents are assumed to have enough information (Allen, 1993), especially about discount rates, preferences, technology and general macroeconomic data. They are supposed to have the necessary resources available to them in order to make rational decisions (see Cochrane, 2005; Hordahl and Packer, 2007; Geanakoplos, 2008). The Consumption Capital Asset Pricing Models (CCAPMs) emphasize the role of technological breakthroughs and preferences, in particular (Cochrane, 2000; Ludvigson, 2013). Overall, the dynamic seen in these models is posited to influence the propensity towards risk or else the aversion to risk (Lucas, 1978).

If the expected rate of return is higher than the risk-free rate, and if the risk premium and the hypothesized covariance between the asset returns and the discount factor seem to make sense, the motivation to invest increases without allowance for possible chaotic behaviors (see Campbell, 2003; Mandelbrot and Hudson, 2004). The market is assumed to work efficiently, failing which, it would be much too risky to invest in additional assets (see Fama, 1963, 1965).

Market imperfections or frictions are no doubt present in the marketplace (Estrella and Mishkin, 1997). However, they are not considered powerful enough to derail the economic and financial systems. Yet, deviations from forecasted predictions have been noted and they are not all minor; rather, major abnormalities have actually occurred, the GFC being a prime example. Consequently, model adjustments have been made (see Brealey et al., 2016). Shiller (1979, 1981) has shown that asset prices have been more volatile than what fundamentals indicated. Various authors also noted that the volatility of the markets is higher than expected (e.g., Mankiw et al., 1985, 1989; West, 1988; Schwert, 2003; Barsky and De Long, 1993). Campbell and Shiller (1988a, 1988b) blame the variation in the dividend-to-price ratio on (1) the variations in expected dividends and (2) the variations in discount rates, with the latter accounting for the largest portion of variation (Cochrane, 2011). Yet, discount rates have been quite stable in the first decade of the 2000s.

[3] An example of such gap is discussed in the concept of the Equity premium puzzle of Mehra and Prescott (1985) and Campbell and Cochrane (1999). See also Claessens and Kose (2017a) for a recent review.

[4] With respect to the Equity premium puzzle, Cochrane (2005, p. 21) notes that an excessively large risk-aversion coefficient of 50 is needed in order to reconcile with the empirical market data. It usually varies between a value of 1 and 5. For more on the coefficient of relative risk aversion, see Rouwenhorst (1995, p. 305).

[5] Behavior, not populations as in the Lotka-Volterra equations. See further below.

[6] Previous attempts have been made at using forms of modification of the Lotka-Volterra equations, in the context of small business firms and private equity firms (Brady, 2017).

[7] We add an element of dynamism to the Lotka-Volterra equations. See further below.

[8] See also Pinto et al. (2015) for a practioners' view of the model.

[9] See Appendix 1, tenet 4: we modified the standard CAPM to account for market imperfections in the context of our predator-prey approach.

This suggests that other factors affected the volatility of the US market. Agarwal et al. (2014) argue the following: "Our finding that eliminating bad lenders had a greater impact on mortgage defaults than eliminating bad loans also suggests that reckless, not predatory, lending practices deserve greater scrutiny" (p. 50). To their way of thinking, the culprit is not so much predatory mortgages or behaviors as it is recklessness. Yet, this recklessness can hardly by itself explain how volatile the 2007–2009 market became, even though it was certainly a factor in the herding effect of the crisis.

Building on the models by Kiyotaki and Moore (1997) and Bernanke et al. (1999), Brunnermeier and Sannikov (2014) point to several factors than promote the amplification of market problems. The economic system is: (1) assumed to be non-linear so that small events can quickly swell; (2) asymmetric; in particular, market lenders are experts while households are in general less savvy, informed and/or wealthy; (4) subject to risk-aversion behaviors that may be driven away from fundamentals; (5) subject to entrapment in misallocation of resources; (6) sensitive to externalities, and; (7) influenced by financial innovation, which motivates experts to hedge their idiosyncratic risk, thus potentially leading to higher systemic risk.

Previous papers have discussed the financial intricacies of toxic products (so-called "Bads"; See Appendix 1). It has been proposed that crises in the financial markets are composed of three moments. The first moment is a herding effect whereby market agents converge without a clear sense of direction towards risky ventures in hopes of quick profits (Sharma and Bikhchandani, 2000, p. 3). The second moment is the swarming effect, whereby market agents behave in a much more organized and focused way and where groups of them launch attacks to gain a decisive advantage. The third moment consists of a stampeding effect; it brings the annihilation of some of the market players to the benefit of those who have played the predator-prey game to the best of their self-centered advantage, using deceit as their key strategic tool.

Each moment is considered to form a deviation from equilibrium, labelled respectively σ_1 (herding),σ_2 (swarming), and σ_3 (stampeding) – see Appendix 1; tenet 1.

Each moment is a manifestation of predator-prey dynamics. Authors have indeed noted that financial predators are present in the marketplace (Bolton and Scharfstein, 1990; Besanko et al., 2014). We emphasize the fact that their interactions with their prey play an important role in explaining economic cycles (Kondratiev, 1926; Schumpeter, 1939), a remark that seems to go against some of the conventional wisdom of micro- and macro-economic theory (e.g., Mas-Colell et al., 1995; Cooley, 1995), which rely on market imperfections to explain some of the market troubles.

When regulations are poor, or, put differently, when they favor the emergence of free riding[10] as well as bad, socially toxic behaviors, the following relationship is assumed:

$$Free-riding = \frac{k}{QBads} \tag{1}$$

where k is a constant we shall use during the course of this paper and *QBads* is the quantity of toxic products. The constant k relates to the ratio between predator and prey behaviors (i.e., not predator and prey populations[11]). Its ideal value has been found to be $[1 + \frac{1}{\pi}]$ or approximately 1.3 (see Appendix 1). In (1), it can be seen that there is a trade-off between free-riding, with its inherent risks of regulatory reprisals, and the selling or buying of quantities of Bads (*QBads*), characterizing a 'badfare' economy. A buyer, for example, may decide to free ride the market quite brazenly while buying few Bads, or else he may choose to buy a large amount of Bads and deceitfully pretend not to free ride. The underlying mechanism of this trade-off is deceit (based on asymmetry of information), which is at the core of predator-prey dynamics. One way or the other, there is abuse, some forms of breach of trust, and some conniving patterns aimed at ensuring self-benefiting gains. In this regard, it has been discussed that the normal distribution curves associated with each sigma σ relate to the interplay between predator and prey behaviors (see Appendix 1).

Our analysis focuses on the "Great Financial Crisis" (GFC) of 2007–2009, an event amplified by the predatory mortgages in the USA during the period (Claessens and Kose, 2017a). The housing sector offers many advantages that are of value when trying to solve the puzzle of investors making the wrong decisions leading to financial bubbles, while it is assumed they are aware of the risks they are facing (Abreu and Brunnermeier, 2003).

Home buying has been known for many decades to be highly dependent on expectations about future income (rent, salary, ability to borrow, etc.), the expected appreciation of the home (Zeldes, 1989; Deaton, 1992; Carroll, 2001; Meghir, 2004; and Jappelli and Pistaferri, 2010), credit growth (Flavin, 1981), agency costs (Carlstrom and Fuerst, 1997), and possibly on the marginal utility function of the buyers (Carroll, 1997).[12] As such, there is an element of uncertainty in home buying. We posit that moderate uncertainty should theoretically not lead to financial crises, unless of course market expectations are positively boosted by the urge to borrow (using houses as collateral), easy credit access,[13] and a reduction in agency costs, a situation best described by the term "debt trap" (see Aoki et al., 2004). This is indeed what happened during the GFC in the US (Mian and Sufi, 2010).

The housing market, which is an important segment of the economy, is sensitive to the same underlying factors that influence the overall economy (Leamer, 2007). The fact that, generally speaking, the housing market displays long lags, makes crises more evident. Its role, factors of influence, associated uncertainty, and inherent bias all provide a fertile ground for analysis.

This is especially true since normally a housing market is not volatile and should not have a poor "signal-to-noise" ratio. By this, we mean that there was noise created during the GFC by way of the teasing rates associated with the predatory mortgages and by the media coverage of the housing market frenzy. What should have been good signals, such as proper credit assessment of the lending firms, were in fact misleading signals. In short, major lenders were over-rated; in the process, this inflated the trust in what would become toxic products, such as Collateralized Debt Obligations (CDOs) and pools of mortgages tainted by high-default risks hidden among regular mortgages (Frame et al., 2008; Gorton, 2008).

Because housing wealth is not easily connected to productive potential compared to equity market wealth, it would make sense that housing wealth would not be as volatile as equity is (Mishkin, 2007), but the GFC proved that under extraordinary conditions, it could be very unstable indeed. From this perspective, market imperfections during the GFC were man-made, and more precisely, predator-made. The Bads (e.g., toxic mortgages) and the debt traps ultimately benefited a few, while penalizing many – the taxpayers who had to foot the bill of the Paulson plan[14] and those who lost everything.

[10] Free riding is defined as the act of abusing common resources or regulations to serve selfish interests, to the detriment of other users of such resources or followers of such regulations.

[11] The difference between behaviors and population is important when dealing with the Lotka-Volterra equations, which focus on populations and not on behaviors.

[12] According to the tenets of the standard dynamic general equilibrium model, households seek to maximize utility while corporations seek to maximize profits (e.g., DeJong and Dave, 2007).

[13] In their analysis, Krishnamurthy and Muir (2017) show that "These results are consistent with the view that expansions in credit supply are an important precursor to crises." (p. 4–5).

[14] On a corporate scale, the likes of Goldman Sachs took advantage of the imperfections while others like AIG or Lehman Brothers, paid the price for such toxic behavior as relying on excess finance premia (Levin and Natalucci, 2005).

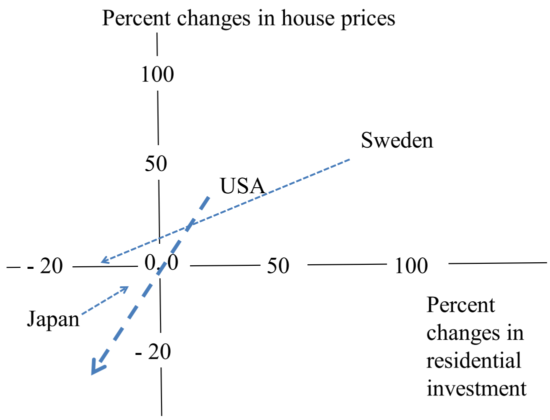


Fig. 1. Movement from the period of 2000–2006 to the period of 2007–2009 in various countries. *Note:* Countries that emulated closely the downfall of the US included: Spain, Ireland, New Zealand, and the UK. Countries with a moderate fall included Canada, Finland, and the Netherlands.

The housing market during the GFC in the US has the peculiarity of amplifying the market imperfections, such as asymmetry of information between lenders and buyers. Fig. 1 describes some changes that occurred in various countries during the years 2007–2009.[15]

Among the various countries, one of the largest movements (declines) was that of the USA. Separately and concerning financial wealth, it has been estimated that a 1% change in equity leads to a change in consumption of approximately 0.05% in the USA. A 1% change in equity value in Japan leads to a change in consumption of approximately 0.02% in Japan and Europe (Bayoumi and Edison, 2003; Catte et al., 2004). Hence, the US market during the GFC shows in clear terms that it reacted strongly; a market may be dysfunctional despite what the standard economic models predict.

We note that the housing market is subject to a home bias,[16] which is the tendency for buyers to purchase in their local area, which theoretically would not make the market as unstable as, say, equity sold on international markets.

In summary, existing economic models have not been able to solve the puzzle of excess or sudden market volatility,[17] for example, in the US housing market, despite the introduction of such concepts as cognitive biases, the herding effect (Lux, 1995) or exchange rate considerations (Coeurdacier and Rey, 2013). The US housing market during the GFC offers a magnified glance at how a market can digress from normalcy (Brunnermeier and Julliard, 2008).

We posit that the unexplained component of market volatility is the presence of predators, or more specifically, the interplay between market predators and prey (see Brunnermeier and Pedersen, 2005). During the GFC, these predators offered toxic products (so-called "Bads"). Packages of Bads were sold on the national and international markets in the form of pooled mortgages (securitization), which then internationalized the local dysfunctional components of the system (Ehrmann et al., 2011; Miranda-Agrippino and Rey, 2015). The economy was to suffer at both ends: (1) home buyers who were nearing or exceeding their credit limits and vulnerable to predatory mortgages lending, and (2) large institutions like Lehman Brothers that could not survive the turmoil and the downfall of the subprime scheme.

The predatory nature of firms has been recognized before the GFC but without delving deep into the root causes of the problem (Milgrom and Roberts, 1982; Mehlum et al., 2003). Over the decades, economic models that have discussed the intricacies between domestic and international factors have not provided an explanation for the puzzle of market agents having been trapped blindly in economic/financial crises (Solnik, 1974; Adler and Dumas, 1983; Uppal, 1993; Engel, 1994; Devereux and Sutherland, 2010).

Hence, we introduce the concept of “predatory cells” as discussed in the next sections in an effort to solve the puzzle of sustained questionable decisions and actions leading to financial and economic crises.

3. The predator-prey dynamics and the modified Lotka-Volterra equations

We posit that the financial markets are influenced by predator-prey dynamics. Predators are those market agents who offer toxic products (Bads), luring their prey with attractive terms, to gain financially to the detriment of these prey, by surprise (thus, through deceit).[18] The prey are the naive investors and fund providers who trust blindly and/or exhibit excess optimism, thinking they can beat the market. The prey are not necessarily and merely the toxic product buyers; an individual may approach a mortgage-loan provider and present him with false or misleading information in order to get a much-anticipated mortgage (“predatory borrowing” – Cowen, 2008). Assuming he meets the criteria set out in the theory of financial predation (the CMFP, see Appendix 1; tenet 2), he too can be a predator. In this particular case, the fund provider is the prey.

In the poisoned, badfare marketplace, Bads take over the Goods, and a parallel economy develops, which is nothing else than a predatory web filled with Bads, that is, with toxic products. It is important to note that Bads are defined as toxic products or toxic information (deceitful information) and more generally as a combination of the two, which of course is a worse case scenario. In order to mislead a homo-economicus, who by definition is a rational individual, a bad product cannot be sold without providing at the same time bad information. Hence, in the context of financial predation, Bads refer to bad products that are accompanied by toxic information. Bads necessarily infer asymmetry of information: the seller of Bads is aware of the toxicity of his product but the buyer is not, at least not completely.

Using the psychological model that pertains to the CMFP, three behavioral states have been known to occur among the market agents (see Appendix 1): cooperation, competition and predation[19] (see Appendix 1; tenet 2). These are exemplified in Fig. 2, as follows:

The model exhibited in Fig. 2 presents some affinities with the underlying psychological constructs of the financial accelerator model (Bernanke and Gertler, 1989; Coric, 2011; Claessens, and Kose, 2017b). The latter emphasizes the role of easy access to credit (which acts as a bait in the CMFP) in normal or expansionary economic periods. As credit is made easily available, and as market prices increase and credit ratings become favorable, the expectations about the future (the expected ROI in the CMFP model) build up, a mechanism that encourages more

[15] Based on data provided by Claessens and Kose (2017a).

[16] For an introduction to the home bias subject and its implications, see Bekaert and Hodrick (2018, chap. 13).

[17] As an example and as noted by Aït-Sahalia et al. (2015), the volatility index VIX from the Chicago Board Options Exchange (CBOE) – the so-called “fear gauge” – reached “levels above 80% at an annualized rate [were recorded] at the height of the financial crisis in the Fall of 2008.” (p. 601). The prior peaks (cerca 1999, 2002) had historically been at around 50%.

[18] For the notion of surprise and its assumed role in financial crises, see Krishnamurthy and Muir (2017). If, indeed, surprise is a key component of financial crises, then mere recklessness cannot be enough to justify the emergence of bubbles, because it would not cause panic. Bad surprises, however, do fuel the fear (perceived risk) of not exiting the market on time. Surprise is a sine *qua non condition* of predation in the CMFP (See Appendix 1, tenet 2).

[19] In the CMFP, trust (confidence) can be considered as inversely proportional to risk aversion. The less trust there is, the more risk-adverse the market agent is.

[43] Government Accountability Office.

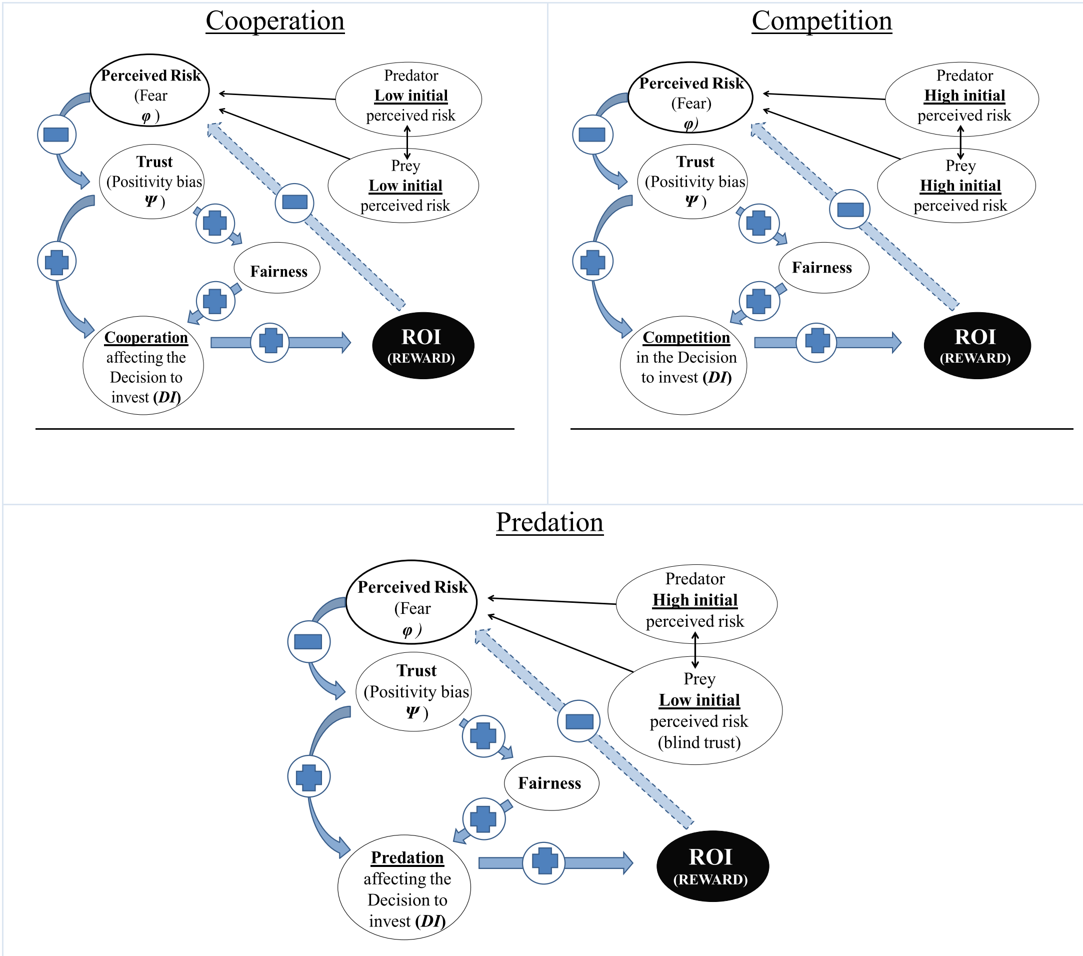


Fig. 2. Psychological moves towards predation. *Notes*: On the top left of Fig. 2, the dynamics are that of cooperation (see the levels of perceived risks explained in the top right bubbles for both predators and prey in the three different scenarios). Perceived risk affects trust in the market negatively, but it is low. Trust is high and encourages cooperation, which translates into investing in the market. The market is assumed to be fair when returns on investment are positive; there are no reasons to perceive it as risky, hence trust is energized and further decisions to invest are taken. On the top right of Fig. 2, the market agents tergiversate. The perceived risk is relatively high for both market agents – sellers and buyers – and trust is shaky. Some believe they are being treated unfairly. Instead of cooperating, they compete, which means they invest in ways that is a race between the two. The first one to win the race is likely to invest more and attempt to grab the entire market. At the bottom of Fig. 2, perceived predation is low for the prey; they then trust blindly. However, the predators know better and abuse this blind trust to serve their own interests, by surprise, causing harm to the prey in the process (GAO, 2004, p. 3, p. 3)[43]. Deceit is at its maximum level.

borrowing by the eager investor (e.g., the home buyer). This creates a cycle that builds on itself, thus fuelling the herding tendency of the market. Put differently, easy access to credit, rising market prices and favorable credit ratings combine to uplift the confidence in the market (trust, or ultimately, blind trust) which then incites market agents to cooperate in the expectations of future financial rewards, which, if they materialize, reduce the negative perception of market risks. A positivity bias builds up that fuels the herding moment of the crisis, a prelude to the swarming and stampeding moments that eventually develop.

The CMFP also shares some common characteristics with the model of Brunnermeier and Pedersen (2009). In the latter, initial gains coupled with expanded funding (easy credit) encourage investors to take riskier positions (thus resorting to blind trust). As prices move away from the fundamentals through speculation, lower margins but higher gains due to the volume of transactions boost the willingness to extend the funding (less perceived risk). The dynamic fuels itself and fosters a herding effect: more and more people want to benefit from the hot (bull) market. When losses appear, however, credit access is harder to get, yet it is needed to cover commitment on existing assets. Positions are reduced while prices remain away from fundamentals. Panic eventually kicks in. The mechanism at play represents what has been called the debt trap, which is part of the predatory web described in the CMFP (see Appendix 1).

To explain further how the model in Fig. 2 actually operates, we first present the original Lotka-Volterra equations as they apply in biology (Lotka, 1920, 1925; Volterra, 1926, 1931):

$$\frac{dx}{dt} = \alpha x - \beta xy \text{ and } \frac{dy}{dt} = -\gamma y + \delta xy \tag{2}$$

where x is the population of prey and y is the population of predators, and where all four coefficients (α, β, γ, and δ) have to be estimated.

Let us set the average population as[20]

$$Avg\ pop = \frac{Pred\ pop + Prey\ pop}{2} \tag{3}$$

By definition, under the standard Lotka-Volterra formulations, the predator population is characterized by a death rate (γ) and the prey population by a growth rate (α). In the examples we provide below, we set the initial population at 100 for reasons discussed further along, when

[20] We use a simplified version of the average population. In its actual form, it should read avg pop = (s_{pred} *Predpop* + s_{prey} *Preypop*)/2; where s_{pred} and s_{prey} are weighting factors meant to eliminate the units of measurements.

we explain the concept of "predatory cells". Let us assume that the predator is the seller of Bads (toxic products such as a toxic pool of predatory mortgages) and the prey is the buyer of such Bads. In our model, the initial populations of predators and prey must necessarily be equal: for the sake of argument, we assume that it takes one seller of at least one Bad and one buyer of that one Bad for the transaction to occur.[21]

We modified the original Lotka-Volterra equations to meet the tenets of the CMFP in order to fit the financial context under analysis (from the original equation (2)), as follows:

For cooperation (when the perceived risk is low for both agents and the positive sign + is in front of each k)[22]:

$$\begin{aligned} Pred\ pop_t &= pred\ pop_{t-1} - death\ rate \times (pred\ pop_{t-1}) + k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + a_t Prey\ pop_t \\ &= prey\ pop_{t-1} + growth\ rate \times (prey\ pop_{t-1}) + k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + b_t \end{aligned} \tag{4}$$

where $k(pred\ pop \times prey\ pop)$ symbolizes the interaction between the predators and the prey[23] and a_t is the accelerator factor that implies a human dynamic of constant improvement, which is found in the marketplace (Claessens and Kose, 2017b). Such accelerators can include technology. To take this example: technology evolves constantly and improves transactions worldwide on a regular basis. The combinations of the signs (+or -) in front of the variable $k(pred\ pop \times prey\ pop)$ is what decides which state the market agents are in: cooperation (+, +), competition (-, -) or predation (-, +).

For competition (when the perceived risk is moderately high for both agents and the negative sign – is in front of each k):

$$\begin{aligned} Pred\ pop_t &= pred\ pop_{t-1} - death\ rate \times (pred\ pop_{t-1}) - k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + a_t Prey\ pop_t \\ &= prey\ pop_{t-1} + growth\ rate \times (prey\ pop_{t-1}) - k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + a_t \end{aligned} \tag{5}$$

And for predation (when the naive buyer does not see the high risk and the seller knows he represents a high risk but hides it; with the signs -, + in front of the respective k's):

$$\begin{aligned} Pred\ pop_t &= pred\ pop_{t-1} - death\ rate \times (pred\ pop_{t-1}) - k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + a_t Prey\ pop_t \\ &= prey\ pop_{t-1} + growth\ rate \times (prey\ pop_{t-1}) + k\ (pred\ pop_{t-1} \\ &\quad \times prey\ pop_{t-1}) + a_t \end{aligned} \tag{6}$$

For the purposes of our data analysis, we set the predators' death rate at 0.08 and the prey's growth rate at 1.2; these numbers are in proportion of what they roughly were during the last financial crisis in the US (2007–2009).[24]

From this predator-prey dynamic, we obtain the following graphs for a k value of 1.3 (Fig. 3).[25]

Taking a closer look at these curves based on the modified Lotka-Volterra equations, and keeping the same parameters, we obtain (Fig. 4).

We can observe that:

(1) The average population can be approximated by a sinusoidal function (which we discuss in the next section)[26];
(2) the average population is very much a modified version of a series of normal distribution curves (See Appendix 1; tenet 1), which tends to show that normal distributions of market agents in the CMFP are actually the result of the dynamics between predators and prey; and
(3) the modified Lotka-Volterra equations produce an average curve that very much emulates the actual market data, but with equal periodicity, an observation that we discuss further below.[27]

Fig. 5 illustrates the average population of predators and prey showing what we call their two "points of ambiguity" along a vector line, as they change over time:

The presence of two points of ambiguity in the same cycle (this is clearer in the unmodified Lotka-Volterra equations) makes the system very active by nature. Yet, market agents seek stability and predictability.[28] As discussed in a previous study (see Appendix 1), the economic system evolves from one point of ambiguity to the next and Bads will always develop, no matter how hard regulators try to eliminate them. More specifically, the economic system is a balance between momentums and points of ambiguity. Toxic products are an economic means of cleansing the market of the weaker elements of the market agent populations. Our take on it is that they are a necessary component of any economic system.

This economic system of Bads also has important consequences with respect to the homo-economicus. As can be seen in Fig. 5 (left side; the most simple scenario to look at), there are two points of ambiguity pass the initial point at which predators and prey engage in a relationship. This means that there are two truths possible at every single moment (hence the ambiguity), so that the market agent can never be sure if he has maximized his utility in the context of a badfare economy (the utility being defined here as the benefit gained from engaging in a predator-prey dynamic, that is, of being deceitful – Akerlof and Shiller, 2015). The two truth positions are, from his rational perspective, an oxymoron. Rationally speaking, one position has to be false, and one has to be true, so that the market agent travels between a full truth (at a value of 100% level of utility) at the initial point of ambiguity (point t_1) and a possibility of full untruth (what could be a full false at a value of 0% utility) at point t_2. Somewhere in between these two extremes, there is an infinitesimal number of possibilities filled with, for example, half-truths. Thus, there is uncertainty, or put differently, ambiguity (Kaya, 2017).

Under uncertainty, if the market agent wants to remain rational and maximize his expected predatory utility, it appears that it is in his best interest to reach the true point of ambiguity as soon as possible. However, as Fig. 5 shows, equilibrium is a moving target due to the dynamics of predator-prey populations. Hence, the Bads eventually bring the homo-

[21] Of course, this assumption is a simplification of reality prepared for the sake of our analysis. In reality, there are several prey for one predator. This is the subject of a forthcoming article. Similarly, the assumption of equal populations of predators and prey (100 in our model) is meant to simplify the analysis. It is based on Dunbar (1992) and our own simulations.

[22] For the sake of simplifying our analysis, we assume that the accelerator factor is the same for the predator and prey populations, set at $a_t = b_t$. In reality, each population, that of predators and that of prey, would have its own accelerator factor (say a_t and b_t). This is examined in a forthcoming article.

[23] For the sake of simplifying our analysis, we assume that the k constant is the same for both populations, that of predators and that of prey, so that, going back to the Lotka-Volterra equations, $\gamma = \alpha = k$.

[24] These values were obtained by trial and error to fit within the CMFP. We ultimately settled for growth and death values found in the US market at the time. See: https://www.census.gov/topics/health/births-deaths.html.

[25] For different values of k, see Appendix 2.

[26] This calls for a Fourrier series, which is the subject of a forthcoming article.

[27] Again, given the parameters we set, including a k value at 1.3 (or $1 + \frac{1}{\pi}$).

[44] See equations (3)–(6).

[28] Technically speaking, a single point of equilibrium as shown in Appendix 1, Tenet 3, results from the interplay between the two points of ambiguity. Kaya (2017) notes: "Second, decision makers want stability. Yet, minute changes in point estimates (…) can result in big changes in final decisions." (p. 165). In our model, those "point estimates" are the two points of ambiguity. Hence, market agents have a keen interest to find equilibrium.

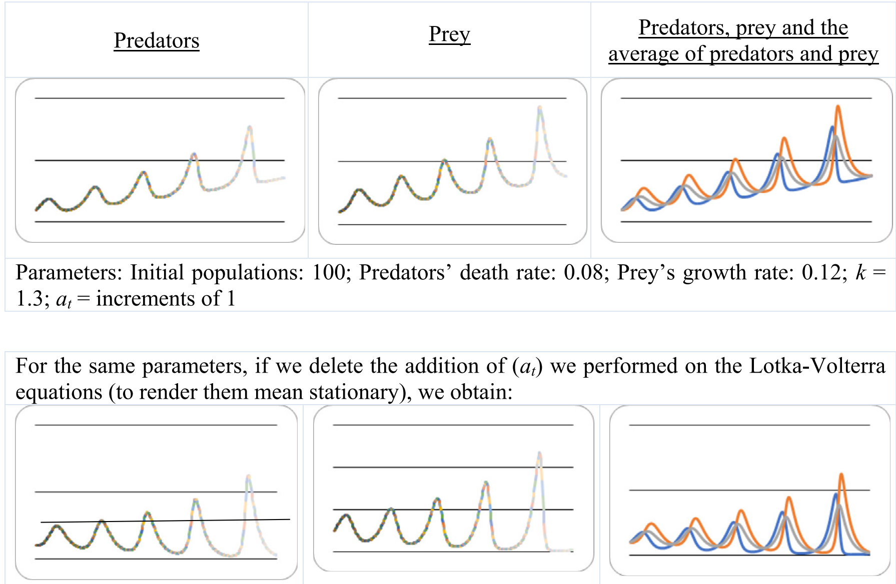


Fig. 3. Modified (dynamic) Lotka-Volterra equations illustrated. *Notes*: On the X-axis is the ordering of time and on the Y-axis is the Population. As can be seen, the modified Lotka-Volterra equations display a tendency to move higher and higher, so that there is an underlying positive tangent rather than a flat baseline with a slope of zero (0). The positive underlying slope in the modified equations emulates how the financial markets have actually evolved over the years and decades.

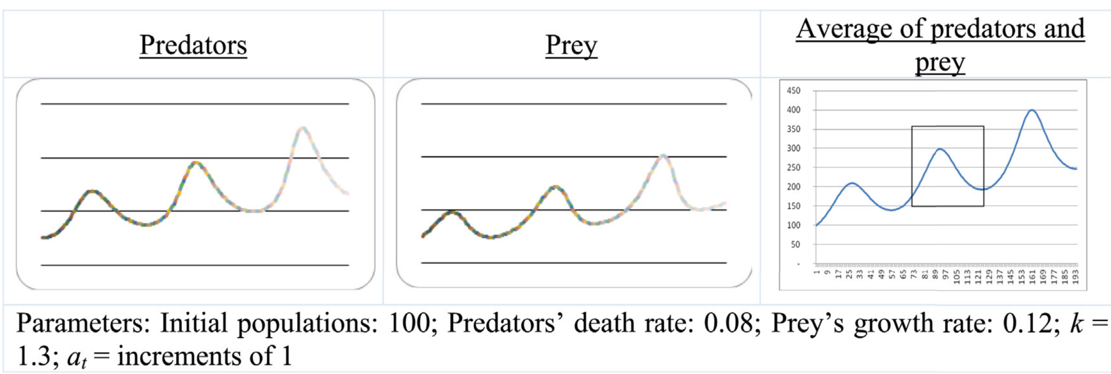


Fig. 4. Modified (dynamic) Lotka-Volterra equations illustrated; a closer look. *Notes*: On the X-axis is the ordering of time and on the Y-axis is the Population. The graph shows that each peak can be considered as a moment of a quasi normal distribution curve. The average curve suggests that the market evolves in a cyclical manner, which is what the Historical Predatory Index (HPI) curve suggests (See Appendix 1).

economicus back to what he is expected to be: rational and utility driven. He cannot behave irrationally over the long-term (two truths). Yet, in order to get to that state of equilibrium, he has to go through the predator-prey dynamics, that is, through a 'badfare' stage,[29] which implies two points of ambiguity and momentum between the two.

The market agent must decide which one between the two points of ambiguity (left side of Fig. 5) is the one with the truest product with the truest information attached to it. This can be expressed in a Bayesian format as follows:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{7}$$

where A is ($QBads = QB$) to buy or sell, and B is the toxic information (TI) related to the Bads.

We rewrite (7) as follows:

$$P(Buying\ QB_{t2}|Toxic\ information_{t2}) = \frac{P(Toxic\ information_{t2})|(QB_{t2} \times P(QB_{t1}))}{P(Toxic\ information_{t1})} \tag{8}$$

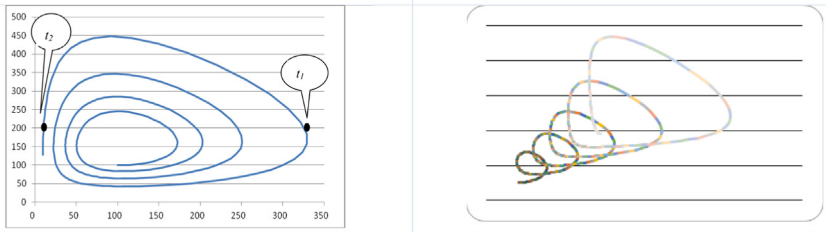
At point t_2 included in (8) and illustrated in Fig. 5, the buyer debates the following: "Should I buy the suspicious Good (actually a Bad) given what I suspect is actually erroneous information regarding this product[30] (e.g., a predatory mortgage or a Collateralized Debt Obligation)"? The probability of purchasing a Bad given the toxic information received at time t_2 is equal to the initial probability of buying the Bads (at t_1, when truth is assumed) multiplied by the probability of receiving toxic information (as the buyer moves towards t_2). This, given the purchasing of Bads that is taking place (at time t_2), all of this divided by the probability that there actually was toxic information at time t_1. The buyer at time t_2 is sensitive to the initial condition that exists at time t_1, which means that retaliation is always possible in this kind of economic (bounded) game.

In the context of blind trust (not believing at all that there was untrue

[29] Previous articles (see Appendix 1) showed that predatory behaviors cannot be avoided and that badfare economies emerge no matter what amount of regulations takes place and is enforced.

[30] See Bond et al. (2009) on how lenders possess at times information about the borrowers' real capacity to afford their much-desired mortgages that, in fact, they cannot afford.

Original (static) Lotka-Volterra equations	Modified (dynamic) Lotka-Volterra equations[44]



Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12; k = 1.3; a_t = increments of 1

Fig. 5. Points of ambiguity with original and modified Lotka-Volterra equations.[44] *Notes*: The number of prey is on the X-axis and the number of predators is on the Y-axis. The graph to the left displays the two points of ambiguity more clearly. This makes for a difficult stand for the market agents: which one of these two points of ambiguity provides the maximum utility? Predators and prey engage in an on-going debate, which makes the points of ambiguity dynamic. The vector graph was created by replacing the time line along the X-axis in Fig. 4 with the number of prey and by putting the number of predators on the Y-axis. This allows us to show that for the same number of predators, along the same vector line, there are two possible populations of prey, which is why we call these points of ambiguity.

information at time t_1 and/or that the Goods were not bad at all at point t_1), the probability of purchasing Bads at the second point of ambiguity t_2 tends to be completely unconstrained by reason. The homo-economicus is thus fooled. For the predators, this means that they have a key strategic incentive to provide toxic information at t_1 so that the prey move to t_2 (momentum) thinking they will reach a new beneficial point of ambiguity. This promise of future benefits through the present feeding of toxic information is typical of predatory behaviors.

This meets the logic that is necessary to explain the opening moment of a financial crisis – the herding behavior. Market agents rush to buy what they believe is good, (at point t_2), which are actually toxic products (Bads) because the information they receive does not lead them to realize the Goods are actually Bads. These naive investors fear that they will miss the opportunity to enter the market. However, as the probability increases that the information that circulates in the market is toxic, the probability of buying the Bads decreases: buyers fear that they will miss the opportunity to exit the market and start to panic (Mun, 2006). Hence, for the archetypal homo-economicus, there is no other way to behave but to exit the market as soon as Bads and related toxic information are discovered. This is very much what happened in 2007–2009. He rationally made the decision to exit the market, even though he did it in a panic because he was under high pressure not to lose everything. Thus, considering Bads as an articulated Bayesian mixture of the product itself and information, we arrive at what can apparently explain the three moments of the financial crises in a 'badfare' economy.

4. The sinusoidal approximation of the modified Lotka-Volterra equations

We estimate that the sinusoidal approximation of the modified Lotka-Volterra equations for the average population,[31] which was found to be $Avg\ pop\ =\ \frac{Pred\ pop\ +\ Prey\ pop}{2}$, is[32,33]:

$$F(a_t)\ =\ (Avg\ pop)_t +\ k\ \times\ sin(a_t) \quad (9)$$

where $F(a_t)$ is an expression of predator-prey dynamic at time t. The accelerator a_t is assumed to grow in increments of 1. At $t = 3$, for example, $a_t = 3$.

When we graphically compare the average population growth developed using the modified Lotka-Volterra equations, to our proposed sinusoidal function and to the Historical Predatory Index (HPI) curve (see Appendix 5), we obtain the following (Fig. 6):

As can be seen in Fig. 6, it turns out that the sinusoidal function of the average population of predators and prey given the set parameters of predators' death rate of 0.08, prey's growth rate of 0.12, $k = 0.5$, an initial population of 100 and an accelerator in increments of 1 (a_t), results in a curve that is remarkably similar to the curve we found in the Historical measure (Index) of Financial Predation – the HPI (see Appendix 5).[34]

More precisely, we can compare the actual values between the real data and the sinusoidal curve found through our modelling effort, as follows (Table 1).

Our analysis shows that the sinusoidal approximation of the HPI market data, which measures the propensity to resort to predatory behaviors, is close, and warrants further analyses. This suggests that the financial markets may respond to specific cycles, at least for the period covered by our analysis. The advantage of the sinusoidal function is that it is a simplified version of the modified Lotka-Volterra equations. If, indeed, this sinusoidal curve approximates how the market behaves, then this means that what it is composed of (the predatory cells with initial populations set at 100, a predators' death rate at 0.08, a prey's growth rate at 0.12; k at 0.5, and the accelerator a_t growing in increments of 1) is enough to explain the gap that exists between reality and what economic models predict. All other explanations, such as teaser rates, risk aversion or structural problems, for example, are imbricated in these values. In other words, predator-prey dynamics play a key role in financial crises. Like in nature, this dynamic fosters mutual adaptation, which in the end guarantees the survival of predators and prey; it encourages their betterment through mutual adaptation.

5. The action potential of the market versus the modified Lotka-Volterra equations

Taking a closer look at the HPI curve, we notice three spikes for the last 40 years, as follows (Fig. 7):

Taken in isolation, each spike has the characteristic of an Action Potential (see Appendix 1, tenet 5; and Appendix 4), which responds to the function:

$$\frac{k-1}{(k-\sigma_m)^{\sigma}} \quad (10)$$

where m is the moment of the crisis ($\sigma_1 = 1 =$ herding, $\sigma_2 = 2 =$ swarming, and $\sigma_3 = 3 =$ stampeding). For $k = 0.5$, 1.3, and 2.3, we obtain the following[35] Fig. 8:

We observe that the k value that best emulates the actual data is 0.5 when looking at the crisis from a static point of view (it starts low, peaks, falls back and settles above the starting point). This means that by the end

[31] This calls for Fourier series, which we will address in a forthcoming article.
[32] For different values of k, see Appendix 3.
[33] We can multiply a noise factor n to k in front of sin(a_t) to introduce some micro-movements along the sinusoidal curve, assuming that this addition thus emulates the noise found in the market place. See Appendix 3.
[45] See equations (3)–(6).

[34] Notably, the sinusoidal function takes into account the periodicity exhibited by the actual data. Based on the above and extrapolating, the sinusoidal curve predicts a next crisis in 2027, everything else being equal (e.g., no wars, no ground-breaking technology, etc.).
[35] For different values of k, see Appendix 5.

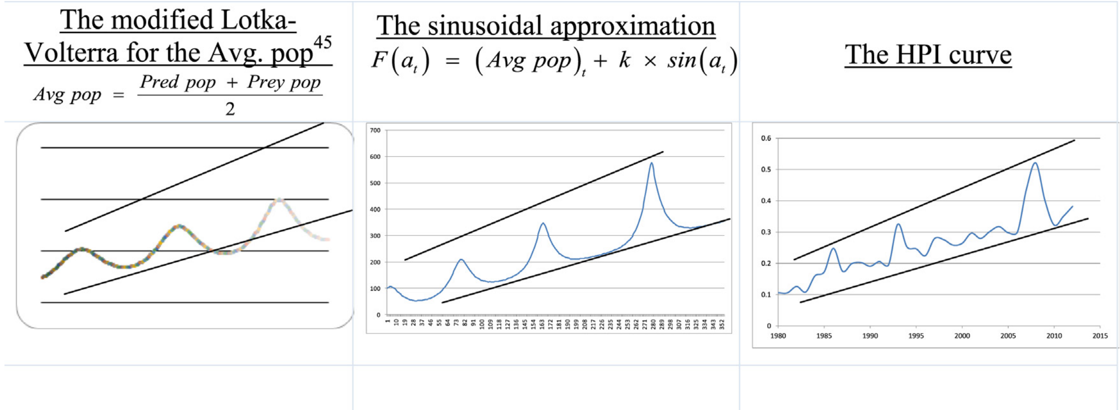


Fig. 6. Psychological moves towards predation.[45] *Notes:* To the left is the modified Lotka-Volterra equation for the average population of predators and prey. It is approximated by a sinusoidal function in the middle graph (for $k = 0.5$) and as it turns out, both graphs provide a close rendition of the HPI curve displayed on the right of above Fig. 6. The slopes that are represented in the modified Lotka-Volterra (left image) and sinusoidal approximation (middle image) curves are the peaks and bottom slopes of the PHI curves (right image), put there to highlight the differences between the various images.

Table 1
Comparing the HPI to the sinusoidal function peaks and X, Y-axes spreads With Initial populations = 100; Predators' death rate = 0.08; Prey's growth rate = 0.12; $k = 0.5$; and a_t = increments of 1.

HPI value (100x)		Sinusoidal function	
Slope connecting the highest points ($y = 1.23x + 5.01$)	1.23	Slope connecting the highest points ($y = 1.82x + 46.5$)	1.82
Slope between the lowest points ($y = 0.76x + 2$)	0.76	Slope between the lowest points ($y = 0.93x + 16.8$)	0.93

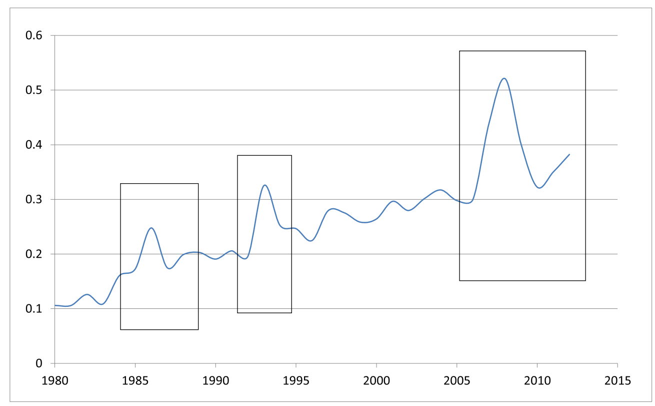


Fig. 7. The Historical Index of Financial Predation (HPI) in the US. *Notes:* this HPI was developed and explained in previous papers (see Appendix 5). It measures the market tendency to resort to predatory behaviors in the US. The X-axis is the year and the Y-axis is the barometer of predatory activity in the market place.

of the crisis, the market is a prey market because the value of k is low[36] (below 1.1). The CMFP predicts that prior to the start of a crisis (prior to sigma σ_1, that of herding), the system is in equilibrium with no signs of herding, swarming or stampeding.

It appears that the equations we have developed (along with their set parameters) help explain the US financial market when we look at it from a predatory perspective. They provide a reason for what would otherwise seem to be exuberant behaviors. Such behaviors are not predicted by the theory of homo-economicus, who is supposed to be rational and welfare utility seeking. We have shown that he actually remains true to form in the sense that his actions are to be considered within the realm of a 'badfare' economy where Bads are bought and sold in the context of greed and panic. Given an ambiguous and toxic environment plagued by asymmetry of information, the market agents nevertheless attempt to remain logical. They engage in herding, swarming and stampeding when conditions, such as easy credit and poor regulations, encourage excesses and a tendency towards a deflating risk aversion. The naive market agents fall prey and lose. The astute and most deceitful ones win and gain. This was exemplified when actors like of Goldman Sachs benefited tremendously from the 2007–2009 crisis and the ensuing Paulson Plan. The market got rid of the weaker market agents and overall kept growing afterwards, ensuring its evolution. Bad was good, for a while at least, and certainly for a portion of the population.

5.1. Predatory cells

Our analysis of predators and prey populations provides preliminary evidence that markets are finite: they are closed dynamic systems where retaliation is possible, thus making the various market agents – sellers, buyers and regulators – more vigilant yet perhaps less able to respond effectively to complex and savvy predatory tactics. In particular, there is an intricate relationship between the population size, the predators' death rate, the prey's growth rate, the financial accelerator a_t, and the k-value. The best relation we could find using the modified Lotka-Volterra equations, the one that most closely matched the US HPI curve, has the following parameters for an ideal k-value of 1.3: population size[37] of 100, a predators' death rate of 0.08, a prey's growth rate of 0.12, and a_t growing in increments of 1. Variations between these parameters are endless, but so far, our research has settled on these values. We have shown that they describe the behaviors of the market agents in the US during the 2007–2009 financial crisis accurately, especially when adjusted in the sinusoidal function that renders predator-prey dynamics with a k value of 0.5 (or ½). This combination of parameters is what we call a "predatory cell".

Our concept of predatory cells may be articulated as follows. Given our initial assumptions meant to simplify the model, in a given market place, an initial group of 100 sellers and corresponding 100 buyers is replicated many times over. Eventually, the group multiplies and all the

[36] Past research has shown that a normal, functional spread for k is between 1.1 and 1.8, while its optimum level is 1.32. Beyond these values, intense predators and prey positions take place and the system becomes increasingly dysfunctional, eventually leading to chaos.

[37] This number is in line with a study by Dunbar (1992).

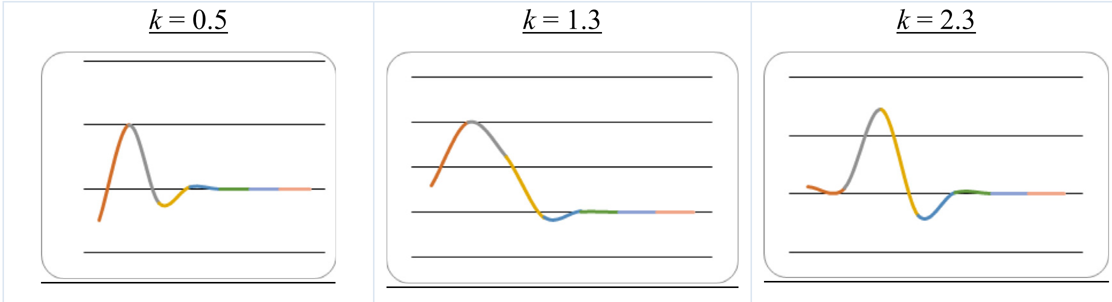


Fig. 8. The Action Potential. *Notes:* The Action Potential expresses the interplay that occurs between a buyer and the seller who responds to the buyer's initial actions. Different values of k change the shape of the curve. On the left side of Fig. 8, the curve starts in the negative, peaks, decreases rapidly, and eventually settles at a level higher than the initial level. In the middle graph of Fig. 8, the curve starts higher than where it eventually lands. In the graph to the right of Fig. 8, the curve ends below where it started, which is contrary to what the modified Lotka-Volterra equations suggest it should do. Thus, the most representative curve of the actual market is the left one, at $k = 0.5$, which is mainly composed of prey.

groups pile up and create the final number of predators and prey that are active in the market, as we conjuncture was the case during that crisis period of 2007–2009. In short, the numbers of predators and prey in the US market at the time were a multiple of that initial predatory cell.

The predatory cells provide an intriguing lens on how a 'badfare' economy emerges. A cancer-like financial cell develops and is soon emulated by other cells through greed, that is, through the fear of missing the opportunity to enter the market that promises to reap fast and large benefits. This mechanism lasts until panic kicks in, which is the fear of missing out on the opportunity to exit the market.

Thus, it is not the law of the strongest that prevails, but rather the law of the best (savviest) predators and prey – prey too have to be astute in order not to become extinct. From this perspective, the mechanics of predation are at the heart of financial evolution, not that of adaptation. Rather, adaptation results from the interplay between predators and prey. Following a crisis (a 'badfare' episode), a homo-economicus resumes his activities as usual until new, potent predatory cells develop, a situation which generally occurs when regulations are weak or lack (l) a firm hold on economic and financial activities, voluntarily or by design.

6. Conclusion

This paper offers somewhat of a debatable conclusion. It states that a 'badfare' economy, or an economy where Bads exceed the Goods, serves a cleansing purpose and thus promotes the evolution of the homo-economicus, albeit it creates victims and is, at first glance, vastly unfair. The most corrupt, devious and deceitful market agents escape the harm of the stampeding moment that ends financial crises while they leave a vast number of prey in their tracks. These market agents, or predators, use or create market imperfections to their advantage, to the detriment of their prey. As such, we propose that market imperfections do not appear in a vacuum; they are the making of the market agents. When they result in a 'badfare' economy, it can be said that the market predators planted them through a mechanism that we call predatory cells, emerging from predator-prey dynamics expressed by modified Lotka-Volterra equations and their associated sinusoidal approximation, under the influence of a constant k. After all, during the GFC, decisions to ease credit on home mortgages, to rate lenders in the most positive way and to accept multiple, shaky house collaterals were made by market agents: they did not appear randomly and out of nowhere.

In our view, Bads are inevitable. There will always be predators and prey. There will always be people willing to deceive others (i.e., willing to sell Bads, that is, toxic goods jointly with toxic information) in order to gain a financial advantage to the detriment of their prey, by surprise. In a system that strives to ensure the evolution of the homo-economicus, there will always be prey who are overly naive, who trust blindly, or else who suffer from a positivity bias that eventually leads them to their demise.

The CMFP seems to have a large number of affinities with existing models, such as that of the financial accelerator, while adding a predatory-prey perspective explaining some of the mechanisms behind market exuberance.

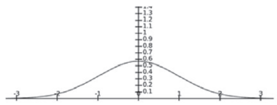
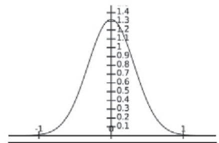
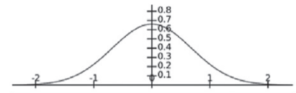
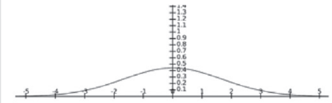
The fact that Bads are ultimately good does not mean measures should not be adopted to reduce the harm committed in the marketplace by cruel predators. Education and regulations are both needed and must be kept up to date in order to outsmart the predators that come with new ways of deceiving the economic and financial systems. It is illusory to believe that the markets will behave for the benefit of all by lowering the levels and executive powers of regulators and/or by limiting education of the market agents. To do so gives way to a "Wild West" of market frenzy, increasing the tendency of predators and prey to herd, swarm and stampede each other. Predatory cells may be dormant and eager to carve a market niche (such as home buying) that will benefit them, to the detriment of their prey, using deceit in the process.

Appendix 1. Key tenets of the consolidated model of financial predation

The following tenets have been discussed in our previous works (e.g., Mesly and Racicot, 2017a; b).

Tenet 1: Financial crisis and its three moments

Moments in a financial crisis are expressed as follows (Fig. A1):

Initial state (equilibrium at the limit or at zero)		Herding (moment 1)		Swarming (moment 2)		Stampeding (moment 3)	
							
$f(x_{\text{limit}})=\frac{k}{2.3}e^{-\frac{1}{2}\left(\frac{x_{\text{limit}}}{k-2.3}\right)^2}$		$f(x_h)=\frac{k}{1}e^{-\frac{1}{2}\left(\frac{x_h-0}{k-1}\right)^2}$		$f(x_s)=\frac{k}{2}e^{-\frac{1}{2}\left(\frac{x_s}{k-2}\right)^2}$		$f(x_p)=\frac{k}{3}e^{-\frac{1}{2}\left(\frac{x_p}{k-3}\right)^2}$	
1.15, 1.15	**1.15, 1.15**	**2.30, 2.30**	1.73, 0	**1.15, 1.15**	1.73, 0.58	0.58, 0.58	0, 2.30
1.15, 1.15	**1.15, 1.15**	0, 1.73	0, 0	0.58, 1.73	**1.15, 1.15**	2.30, 0	**1.73, 1.73**

Legend: Where the above table is structured as follows:	*Sellers sell Goods*	*Sellers sell Bads*
Buyers buy Goods	*E.g. 1.15, 1.15*	
Buyers buy Bads		

Fig. A1. The three Moments of a financial crisis.

Each moment presents its own distribution curve, which is a function of *k*, as found in previous studies. The initial Point of Equilibrium (at x_{limit}) offers a fair solution for the buyer and seller, yet, it seems sub-optimal for each one. As can be seen, there is an incentive for both to sell and buy Bads, even though during the herding moment, they can both achieve an even better position (2.3, 2.3), but this position comes with the risk of losing everything (0,0). It is tempting to move from one Point of Equilibrium to another one given that there is a possibility to be in a better position (from 1.15 to 2.3), gambling the other market agent will not retaliate or will not realize he has been duped.

Tenet 2: The psychological framework of the market agents and the predatory web

Market agents behave according to the following well-tested model (Fig. A2):

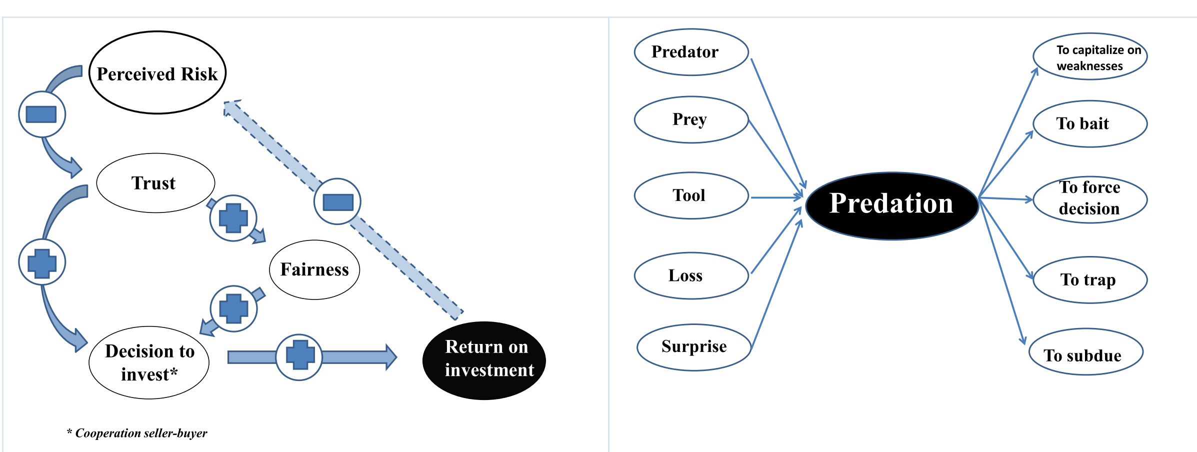


Fig. A2. The CMFP in its psychological format with the predatory web.

The left side of Fig. A2 shows that when the market agents believe there are fewer risks when they interact in the market, they tend to trust each other, possibly embracing blind trust altogether (Smythies, 2009; Loughran and McDonald, 2011; Dezsö and Loewenstein, 2012); the perception of real risk is hence lessened (Odean, 1998). As trust builds, they are more motivated and the investors feel confident they should invest, given that they feel they are, generally speaking, treated fairly. As returns on investments justify the decision to invest, there are fewer reasons to be suspicious. With less perceived risks, trust augments and the cycle builds up but may eventually fall into blind trust.

This cycle has a downside. What if, as an example, the seller of financial products provides misleading information and toxic goods? In order to attract the potential prey in his web of deceit, the seller must trick the one buyer who was developing blind trust. The following elements are necessarily required to build a predatory web: a predator, a prey, a tool (a "Bad" deceitfully presented as a great opportunity), economic harm eventually done to the prey, and a surprise effect (the prey did not realize he was actually buying a Bad). However, to activate the predatory web functionally, the following or some of the following must be present: the predator identifies the vulnerabilities of his prey (e.g., credulity). He baits him with what seems to be attractive terms and/or promises. He pressures the prey to make a decision and act upon it. He traps him with a binding agreement that would be costly to get out of. Finally, he subdues his prey in the sense that he forces him to do what serves best his selfish interests.

The predatory web is thus composed of five structural and five functional components. Once caught in the web, it is difficult and costly for the prey to get out of it.

Tenet 3: Sellers, buyers and regulators and their bounded relationships

Fig. A3 shows that the relationships between the three core market agents – sellers, buyers and regulators – are expressed in a frame that illustrates their bounded rationality. The frame has limits by definition; the economic activity is bounded by a minimum level and a maximum level. This is evidenced, for example, by the constraints that affect homebuyers (see Iacoviello, 2004; Davis and Van Nieuwerburgh, 2015; Piazzesi and Schneider, 2016).

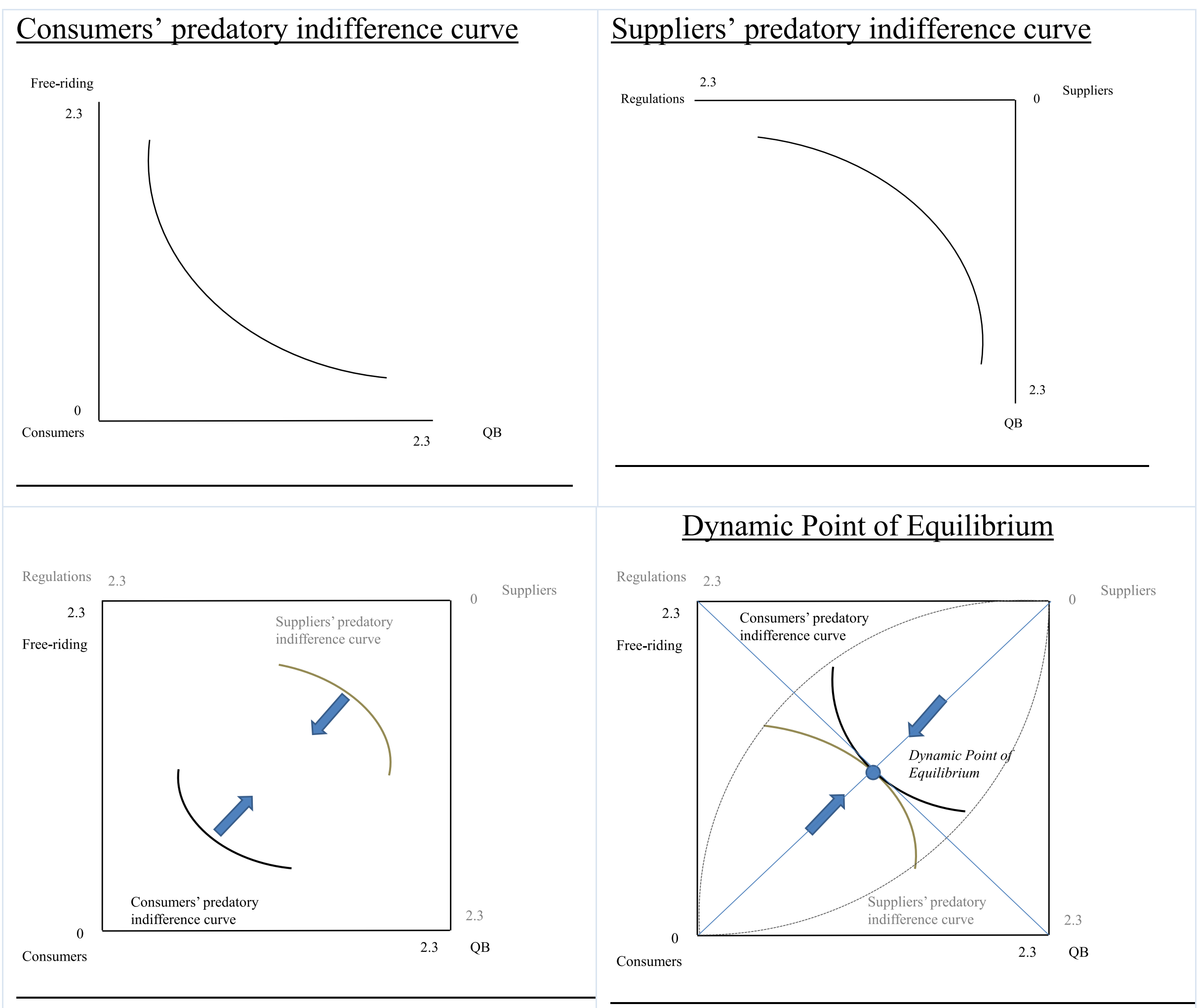


Fig. A3. The relationships between sellers, buyers and regulators.

The above graphs in Fig. A3 read as follows. In a 'badfare' economy, consumers trade between buying Bads and free-riding – taking advantage of the system such as avoiding paying income tax. They may free-ride and dedicate less time to making the efforts to buy the Bads or else they buy more Bads and spend less leisure time allocated to free-riding (which is a form of deceit). Suppliers trade between tricking the regulations and buying Bads. They may pretend to abide by the regulations and sell fewer Bads or else they may sell more Bads and be less inclined to respect the regulations (or else, there are indeed fewer regulations in the market and they take advantage of this to sell more Bads). As discussed in the core text of the present paper, this point is dynamic and actually results from the interplay between two points of ambiguity.

Buyers, suppliers and regulators meet in this ‘badfare’ economy as represented by an Edgeworth box (bottom left corner of Fig. A3). The Consumers' Predatory Indifference curve tends to move upwards as consumers (homo-economicuses) want to maximize their utility (the utility of their predatory behaviors). The same phenomenon applies to the Suppliers Predatory Indifference curve. There comes a Point of Equilibrium, in the middle of the Edgeworth box, where both curves meet.

Should each market agent go pass the Point of Equilibrium, away from their own points of origin, they then each trespass on the other's territory and participate actively in predation. However, to buy more Bads, the consumers have to borrow money and thus get squeezed into a debt or “poverty” trap (Mehlum et al., 2003). The sellers fall into a trap of their own: they have no choice but to deceive more and more in order to hide their mischief. This environment becomes, of course, highly toxic.

Tenet 4: Decision to invest

One crucial tenet of the CMFP is the fact that the market agents must make some decisions. For example, they must decide if they try to stay at the same point of ambiguity or else if they move to a second one that seems more promising. The predator will invite the prey to enter into a momentum towards an alleged better point of ambiguity because that is how he can take advantage of him. The decision to invest has been found to be a modified CAPM equation, as follows:

$$DI = E(r_a)(k + \psi^{\varphi}) \tag{A2.1}$$

Where

$$E(r_a) = r_f + \beta_a\left[E(r_m) - r_f\right] - QBads_{t+1} \tag{A2.2}$$

where r_a is the return on asset a; r_m is the market return; and r_f is the risk-free rate. In the above equation (A2.2) the first part describes the propensity to invest (the original CAPM model) and the second part the aversion to risks (- $Qbads_{t+1}$).

where:

$$\psi^{\varphi} = \left(\frac{\sigma_t}{3}\right)^{\sigma_t/\sigma_m} \tag{A2.3}$$

where ψ corresponds to blind trust or equivalently the positivity bias or the investor's belief that he can beat the market; φ refers to the investor's fear of missing out on the opportunity (to enter or exit the market). $\sigma_t =$ standard deviation of the moment *t* (herding (*h*), swarming (*s*), or stampeding (*p*) and $\sigma_m =$ is the actual deviation in the market place.

QB_{t+1} ($QBads_{t+1}$) is measured by a logistics function:

$$QB_{t+1} = k\ QB_t + (1\text{-}QB_t) \tag{A2.4}$$

The positivity bias ψ, which corresponds to blind trust, is included in the stylized CAPM decision equation, which also includes a role for chaos, that is, for the presence of *QBads*. The market agents, whether predators or prey, choose a course of action based on what they perceive they can gain in order to guarantee their survival *versus* what potential costs may be incurred, with the costs being a chaotic function related to *QBads* (*QB*). They want to maximize their utility, and as the CMFP predicts, this utility is defined in a ‘badfare’ economy by Suppliers and Consumers' Predatory indifference curves (See Appendix 1; tenet 2).

As inferred from the core text of the present paper, the probability of buying *QBads* at the time $t+1$ (or, if we position ourselves on the second point of ambiguity QB_{t2}) is:

$$P(Buying\ QB_{t2}|Toxic\ information_{t2}) = \frac{P(Toxic\ information_{t2})|(QB_{t2} \times P(QB_{t1}))}{P(Toxic\ information_{t1})} \tag{A2.5}$$

These equations show that the market agent is under the influence of *k*, and is sensitive to the initial conditions (t_1, the first point of ambiguity, or simply *t* in general). His expectations take into account what he can gain *versus* what he can lose (QB_{t+1}). He does not know what QB_{t+1} is but estimates it to the best of his capacity much like a player in a poker game bets on what he thinks the other player has in his hands. This is reflected in equation (A2.4).

His overall judgment is affected by a positivity bias (thinking he can beat the market) and his fear of not entering the market on time or not exiting the market on time. This is expressed in equations A2.1 and A2.3. The *k*-value present in equation (A2.1) reflects the fact that he is prepared to invest, otherwise there would be no reason to even consider investing. This motivation to invest is a reflection of his assessment of his predatory capacities over his prey-related weaknesses (*k* is the ratio of predator over prey in terms of psychological behaviors). The *k*-value is influenced (boosted or reduced) by his positivity bias which is exponentially boosted by the perceived risk (fear of entering or exiting the market on time). He measures his chances of success by estimating his deviation *versus* that of the market: if he feels comfortable he can beat the market, then his fear (or, put differently, the perceived risk) is reduced. He is confident he can win and thus invests.

Tenet 5: A financial crisis and its Action Potential

The Action Potential of market crises is illustrated as follows (Fig. A5):

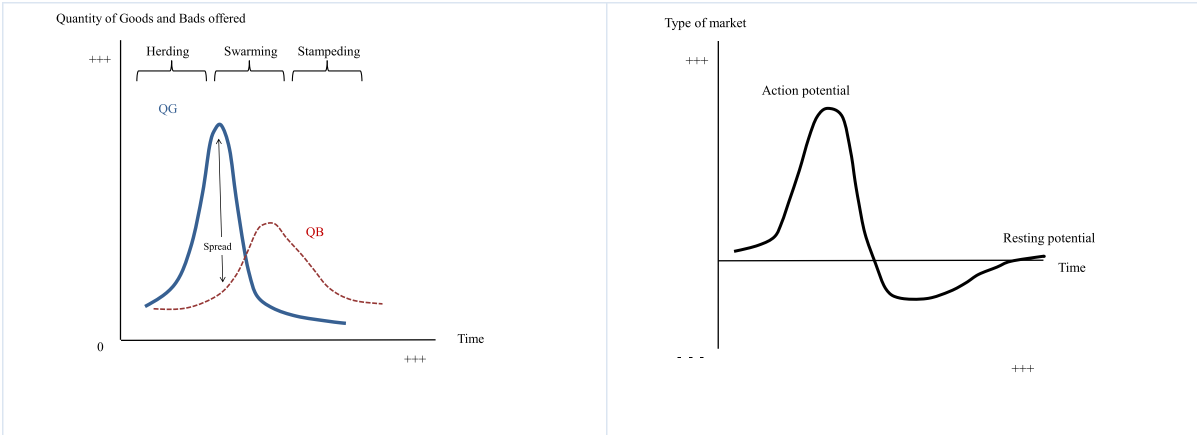


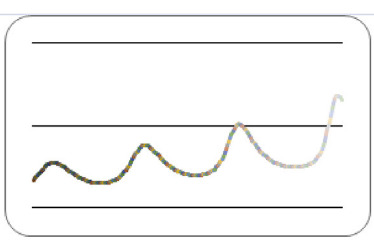
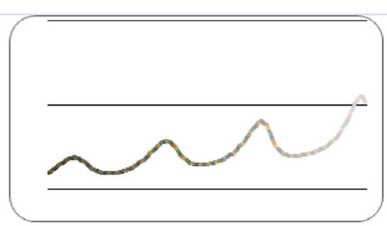
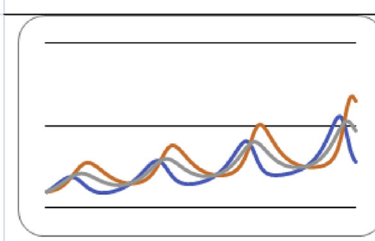
Fig. A5. The Action Potential.

These two graphs in Fig. A5 show how an individual Action Potential is created through the three moments of a financial crisis. The spread between the Goods and the Bads that are offered is positive at first, and then becomes negative. Another way of looking at this is to consider the Goods curve as the Marginal Product curve, produced by having Labor on the X-axis and Total Goods on the Y-axis. There is one for the consumers (the one that peaks first) and one for the supplier, who responds to the consumers' demand with somewhat of a time delay. Initially, both curves rise and both agents are content. However, eventually, the marginal quantities slow down for both due to fatigue or inefficiencies (such as misinformation) and eventually they both see their marginal production of Goods slow down and decrease. That is when Bads take over. The fact that eventually a resting point is achieved testifies to the fact that the market has managed to control the number of Goods and Bads, usually through regulations and, possibly, economic rescue plans such as the Paulson Plan.

Appendix 2. Various values of the K constant for the modified (dynamic) Lotka-Volterra equations

Below, we provide various values of the k constant for the modified (dynamic) Lotka-Volterra equations to show the impact of k on these equations[38]:

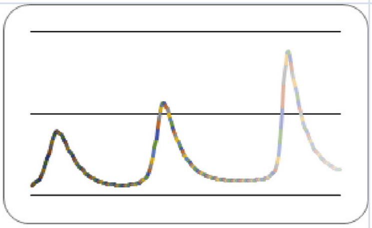
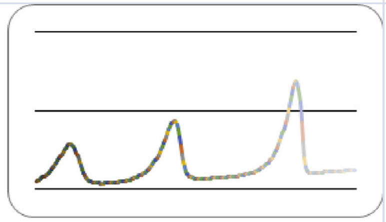
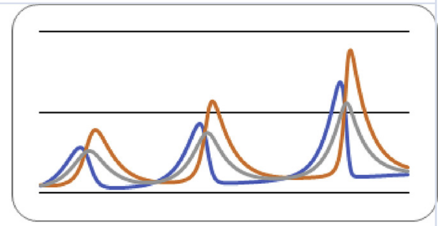
Base measure at $k = 1.3$:

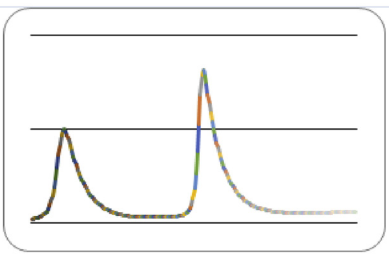
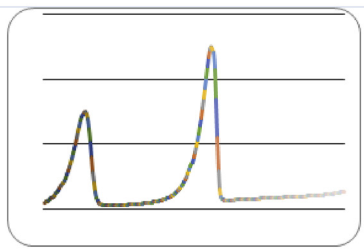
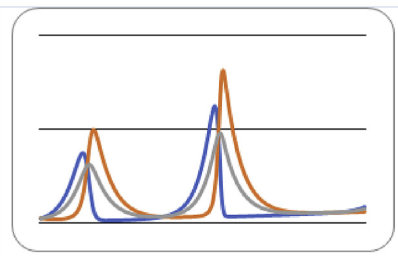
Predators	Prey	Average predators and prey
		
Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12; k = 1.3; a_t in increments of 1		

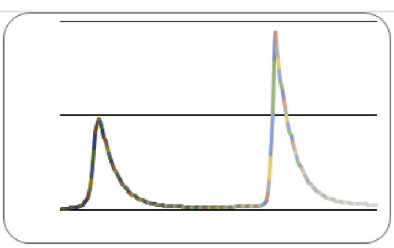
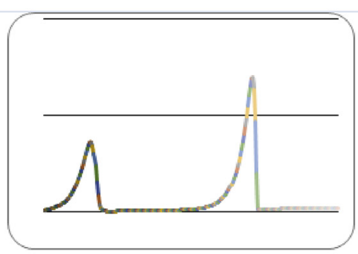
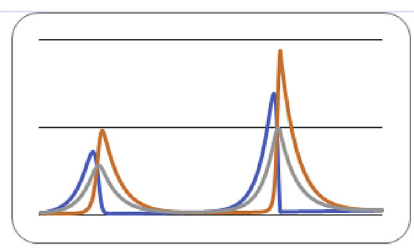
Note: On the X-axis is the ordering of time and on the Y-axis is the Population.

Above $k = 1.3$:

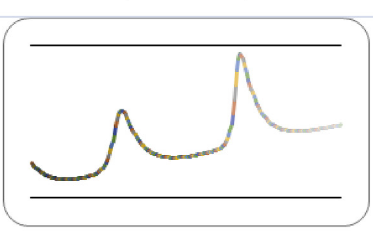
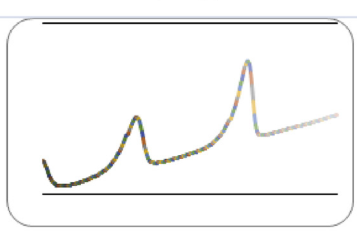
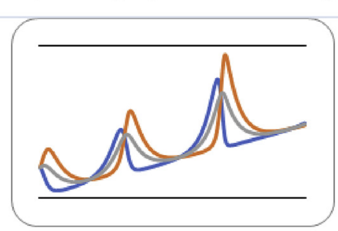
[38] These results are based on Excel simulations. Full data and spreadsheets can be made available upon demand to the authors.

Predators	Prey	Average predator and prey
		
Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12; k = 2.3; a_t in increments of 1		

Predators	Prey	Average predators and prey
		
Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12; k = 4.0; a_t in increments of 1		

Predators	Prey	Average predators and prey
		
Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12; k = 7.0; a_t in increments of 1		

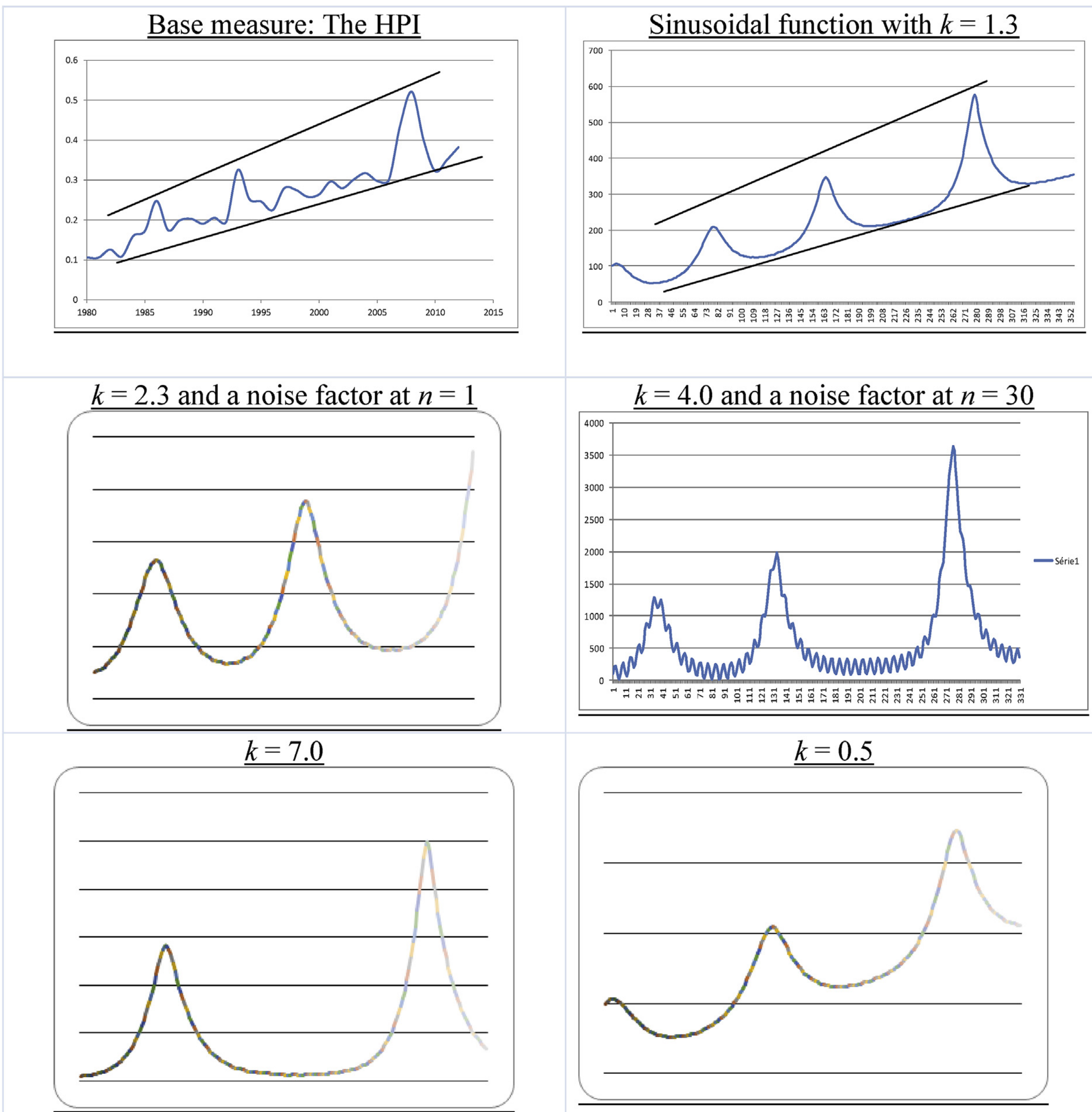
Below $k = 1.3$:

Predators	Prey	Average predators and prey
		
Parameters: Initial populations: 100; Predators' death rate: 0.08; Prey's growth rate: 0.12: 0.08; k = 0.5; a_t in increments of 1		

As a general observation, it can be noted that the k value that best emulates the actual data expressed in the Historical Predatory Index (HPI) is 1.3 (see section "The action potential of the market *versus* the Lotka-Volterra equations" in the core text above). It must also be noted that the more predatory the market is (the higher the values of k are), the higher the peaks in populations of predators and prey, which tends to be in line with the three moments of a financial crisis as the CMFP sees it. As it turns out, at the beginning of a crisis, there is a sudden and rapid rise of predators, which is indicative of a higher k, which by definition spells trouble. Higher values of k carry all the characteristics of toxicity, with abusive and free-riding behaviors by the predators and blind trust by the prey. Toward the end of the crisis, the number of prey accumulates, the US financial crisis of 2007–2009 being a prime example.

Appendix 3. Shapes of the approximated sinusoidal curves for different values of K *versus* the HPI

Below, we provide various values of the k constant for the sinusoidal function derived from the modified Lotka-Volterra equations, to show the impact of k on this function[39]:

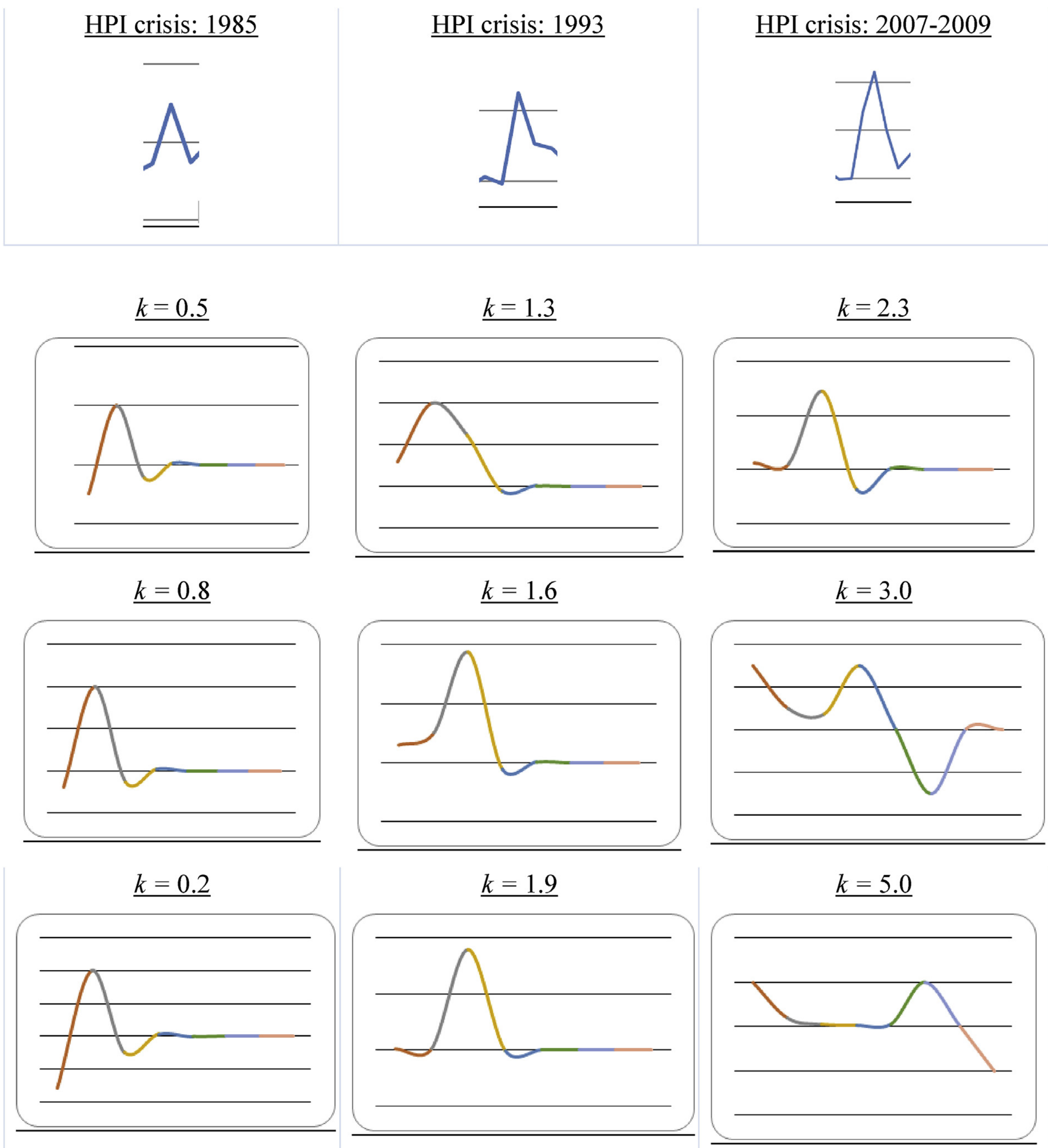


We observe that given the established death rate of the predators' population of 0.08 and the growth rate of the prey population of 0.12, at given an initial population of both groups of 100, $k = 0.5$ provides the closest approximation to what has happened in the US market for the last 40 years or so.

[39] These results are based on Excel simulations. Full data and spreadsheets can be made available upon demand to the authors.

Appendix 4. Different values of *K* for the action potential equation

Below, we provide various values of the *k* constant for the Action Potential function, which is a snapshot of the modified Lotka-Volterra or of the sinusoidal equations, to show the impact of *k* on this function[40]:



We observe that the *k*-value that best represents what we find in the US market according to the HPI is 0.5. This means that the *k*-value has moved from its ideal (functional) level of 1.3 to a level less than half this value, a level that conveys a low ratio of predatory behaviors (not population) over prey behavior (not population). In other words, the market has moved from a functional level to an overloaded prey market, which accurately describes the dire state of the US market in 2009. (The financial bailout plan known as the Paulson Plan had only recently been signed into law, in October 2008). . While the crisis was emblematic of a highly toxic environment, it served a purpose: evolution of the HPI curve shows that the economy eventually stabilized and assumed a historical level of economic growth, in preparation for the next up-coming crisis, predicted by the modified (dynamic) Lotka-Volterra functions and its associated sinusoidal approximation. We posit that while these crises are disastrous, from at least one perspective they are

[40] These results are based on Excel simulations. Full data and spreadsheets can be made available upon demand to the authors.

good for the economy: they cleanse the market of the weaker agents (the ones most susceptible to predation).

Appendix 5. Historical Predatory Index (HPI)

The HPI is calculated by using key macro-economic data (in our study, US data), which we assembled into three groups, each with their own characteristic.[41]

Main characteristic	Sub-category	Examples of applications in the financial world
Bounded time	Horizon	Maturity, holding period, Time Value of Money, Net Present Value, Future Value
	Cycles	Cycles, periodicity, Kondriateff/Presidential cycles, Elliot waves, coupon frequency
Triggered Spin	Gamma (γ)	Interest rate (for return on investments), diversification, return, yield, hedging, convexity, greed, speculating, bull market, expansion, call > put (positive sentiment)
	Lambda (λ)	Interest rate (applied onto debts), inflation, taxes, sensitivity, biases, bankruptcies, foreclosures, panic, bear market, material adverse change, contraction, put > call (negative sentiment)
Layered risk	External	Market condition, systematic risk, risk-free rate, uncertainty, productivity, competition, industry decline, substitute products, low barriers to entry, risk-free rate, primary/secondary markets
	Internal	Unsystematic risk, liquidity, credit rating, propensity to default, real or potential debt, confidence in management, liabilities, sensitivity to cycles, personal history, leverage municipal bonds => stocks => futures => derivatives => hedged funds), single/dual currency, covenants, floating/fixed rate bonds, rollover risk, negotiable/non-negotiable certificates of deposits, traditional/alternative investments, waterfall structure, tranches

HPI summary of key indicators[42]

Year	Horizon	Cycles	Gamma*	Lambda*	External risk*	Internal risk*	HPI Total	HPI average
1971	0,00015	0,02585	0,07883	0,00827	0,07307	0,57833	0,75641	0,12607
1972	0,00042	0,18844	0,06189	0,00258	0,07655	0,71285	0,93496	0,15583
1973	0,00154	0,13655	0,12172	0,00072	0,08906	0,14115	0,87519	0,14587
1974	0,00481	0,16462	0,18227	0,00107	0,09862	0,23767	1,01891	0,16982
1975	0,00582	0,00000	0,11963	0,00259	0,10901	0,30453	0,35420	0,05903
1976	0,00718	0,22709	0,10101	0,00310	0,10914	0,42171	0,75153	0,12525
1977	0,00662	0,32704	0,08115	0,00143	0,11427	0,45750	0,86863	0,14477
1978	0,00372	0,20081	0,10647	0,00000	0,12714	0,30464	0,84295	0,14049
1979	0,00583	0,12697	0,17962	0,00063	0,13497	0,24634	0,78794	0,13132
1980	0,01284	0,09388	0,50370	0,00179	0,16761	0,00000	0,63584	0,10597
1981	0,01198	0,06740	0,34405	0,00434	0,18666	0,01188	0,63479	0,10580
1982	0,01530	0,07026	0,37629	0,00667	0,21037	0,26290	0,75619	0,12603
1983	0,02035	0,09322	0,37991	0,00607	0,22531	0,29274	0,65213	0,10869
1984	0,02054	0,08831	0,76386	0,00543	0,24961	0,31649	0,95985	0,15997
1985	0,03089	0,11112	0,17845	0,00525	0,26614	0,41147	1,03549	0,17258
1986	0,02802	0,13057	0,23265	0,00560	0,28289	0,49449	1,48650	0,24775
1987	0,03619	0,15603	0,23459	0,00579	0,28775	0,51738	1,04823	0,17470
1988	0,03088	0,15070	0,15600	0,00618	0,31779	0,47970	1,19435	0,19906
1989	0,03153	0,13485	0,31022	0,00566	0,36933	0,34016	1,21656	0,20276
1990	0,03602	0,15428	0,27191	0,00778	0,39020	0,25744	1,14484	0,19081
1991	0,03337	0,17805	0,26326	0,00901	0,41235	1,00000	1,23495	0,20582
1992	0,02375	0,20950	0,22255	0,01003	0,42912	0,63051	1,17285	0,19548
1993	0,02543	0,23335	0,35729	0,01122	0,43518	0,48124	1,95133	0,32522
1994	0,03692	0,19885	0,17317	0,01309	0,44258	0,50672	1,51482	0,25247
1995	0,04117	0,16813	0,43311	0,01528	0,44032	0,56514	1,47848	0,24641
1996	0,05133	0,17632	0,35725	0,02029	0,42947	0,61102	1,34880	0,22480
1997	0,05804	0,18121	0,16269	0,02640	0,41683	0,65382	1,67624	0,27937
1998	0,05632	0,18370	0,21490	0,03097	0,38593	0,67156	1,65306	0,27551
1999	0,10402	0,23247	0,33331	0,03095	0,39471	0,59396	1,55024	0,25837
2000	0,10623	0,22517	0,20473	0,03270	0,41420	0,47222	1,58486	0,26414
2001	0,12118	0,32137	0,17986	0,03468	0,44772	0,43349	1,77833	0,29639
2002	0,08270	0,44829	0,10624	0,03829	0,46087	0,49157	1,67837	0,27973
2003	0,09185	0,59366	0,10426	0,04114	0,47791	0,54600	1,81059	0,30176
2004	0,10337	0,72376	0,15381	0,04599	0,49713	0,62043	1,90343	0,31724
2005	1,00000	0,52628	0,10709	0,04953	0,51787	0,59895	1,78743	0,29790
2006	0,46083	0,37872	1,00000	0,05255	0,58186	0,48644	1,79946	0,29991
2007	0,99501	0,36109	0,03610	0,06012	0,73344	0,00000	2,63454	0,43909
2008	0,18680	0,54380	0,19466	0,06601	0,80552	0,01170	3,12547	0,52091
2009	0,10662	0,57785	0,07806	0,07044	0,85156	0,09456	2,40253	0,40042
2010	0,12124	0,66978	0,00809	0,07617	0,90022	0,18752	1,93448	0,32241
2011	0,09947	0,90030	0,00316	0,08113	1,04163	0,81986	2,10153	0,35025

Note: The * indicates that these variables are adjusted for year.

[41] The full actual data (including market data over the last 40 years ranging from interest to inflation rates, to employment levels, GDP and population sizes among other variables) and how the HPI has been composed with its justification, the simulation Excel sheets (several of them) and Monte Carlo simulations can be made available on demand.

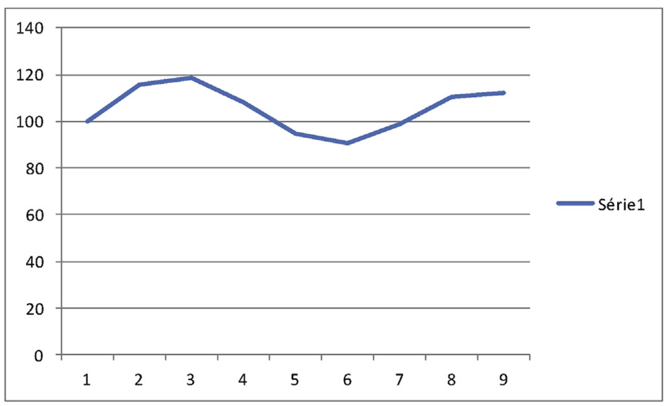
[42] The full actual data (including market data over the last 40 years ranging from interest to inflation rates, to employment levels, GDP and population sizes among other variables) and how the HPI has been composed with its justification, the simulation Excel sheets (several of them) and Monte Carlo simulations can be made available on demand.

Example of Excel spreadsheet simulation:

							startingPopulation			0,5	k		
	Pop prey	Growth rate		Coevolation	death rate					2	0,002		
		0,12		0,002	0,08		100						
	Prey	growth rate			Coev	Pred	Pred*Prey	Coevolution	Pop Prey	death rate			
0	100,000					100,000	10000,000						
1	92,000	0,12	12	112,000	0,002	112,000	10304,000	20	92,000	0,08	8,000	92,000	112,000
2	82,432	0,12	11,04	103,040	0,002	123,648	10192,552	20,608	82,432	0,08	8,960	103,040	123,648
3	71,939	0,12	9,89184	92,324	0,002	134,141	9649,953	20,385104	71,939	0,08	9,892	113,756	134,141
4	61,271	0,12	8,6326483	80,571	0,002	142,710	8744,045	19,299906	61,271	0,08	10,731	123,410	142,710
5	51,136	0,12	7,3525774	68,624	0,002	148,781	7608,069	17,488089	51,136	0,08	11,417	131,293	148,781
6	42,056	0,12	6,136316	57,272	0,002	152,095	6396,521	15,216138	42,056	0,08	11,902	136,879	152,095
7	34,310	0,12	5,0467374	47,103	0,002	152,720	5239,808	12,793043	34,310	0,08	12,168	139,927	152,720
8	27,947	0,12	4,1171807	38,427	0,002	150,982	4219,562	10,479616	27,947	0,08	12,218	140,503	150,982

	Pop prey final	Augmented Pop Prey final	Pop pred final	Augmentd Pop Pred final		Augmented Pop Prey final	Augmentd Pop Pred final	Pop average augmented	t	sin(t)	k	ksin(t)	noise factor n	n *ksin(t)	Popavg + n*ksin(t)
0	100,000	100,000	100,000	100,000	100,000	100,000	100,000	100,000	0,000	0,000	0,500	0,000	1,000	0,000	100
1	92,000	93,000	112,000	113,000	99,000	93,000	113,000	103,000	1,000	0,841	0,500	0,421	30,000	12,622	116
2	82,432	84,432	123,648	125,648	96,837	84,432	125,648	105,040	2,000	0,909	0,500	0,455	30,000	13,639	119
3	71,939	74,939	134,141	137,141	93,673	74,939	137,141	106,040	3,000	0,141	0,500	0,071	30,000	2,117	108
4	61,271	65,271	142,710	146,710	89,751	65,271	146,710	105,991	4,000	-0,757	0,500	-0,378	30,000	-11,352	95
5	51,136	56,136	148,781	153,781	85,351	56,136	153,781	104,959	5,000	-0,959	0,500	-0,479	30,000	-14,384	91
6	42,056	48,056	152,095	158,095	80,736	48,056	158,095	103,075	6,000	-0,279	0,500	-0,140	30,000	-4,191	99
7	34,310	41,310	152,720	159,720	76,113	41,310	159,720	100,515	7,000	0,657	0,500	0,328	30,000	9,855	110
8	27,947	35,947	150,982	158,982	71,626	35,947	158,982	97,465	8,000	0,989	0,500	0,495	30,000	14,840	112

Output on nine periods (0–8 included).



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