Flexible Innovation and Policy under Uncertainty

Working paper –Theme I (D.2.1.)

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Success in today's knowledge economy depends on the strategic use of intangible assets and on flexible innovative policies. Europe's efforts to enhance innovation and intangible investments can be supported more effectively with the use of real options or option-based analysis to help address challenges posed by uncertainty and flexibility in innovation. Several related issues merit attention. What makes innovation and policy design more valuable? What are the roles of uncertainty and competition in innovation and economic policy? When should one compete for exclusive benefits or collaborate? How should one think about innovation and flexible policies and proactively manage innovation and policy risks? What is the impact of market extreme uncertainty on macroeconomic outcomes and policies?

This working paper focuses on developing flexible policies for innovation under uncertainty and examines the role and impact of uncertainty on macroeconomic outcomes and policy initiatives in the U.S. Such policies, whether at the national or firm level, are often based on long-term forecasts (e.g., of demand levels, growth, rival plans) and are typically decided via commitments up front. However, extreme scenarios cannot be ruled out in innovation and policy settings. One issue is how can provisions be built in to protect against overoptimistic (or unlucky) projections while enabling the future by allowing flexibility to alter the scale, use or functionality as demand, needs or future preferences change? Uncertainty of tomorrow changes the value of alternative choices today. Flexibility in innovation policy can enable dealing proactively with risk and high uncertainty. Flexible policies presuppose a richer set of decision criteria, enabling conditional staged future decisions. We suggest that real options analysis can be used to provide a guide for flexible strategies and simulation of innovation policy scenarios. In what follows, we focus on two important aspects: (1) the strategic choice of when to pursue exclusionary competing

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strategies or cooperate in innovation, and (2) the impact of economic uncertainty on real economic activity and policy outcomes based on U.S. data.

1 Competition vs. Cooperation in Innovation

In this section we deal with the real-life situation that many investment opportunities (unlike financial options that are exclusive to their owner) can be exercised in a way that is either aggressive towards competitors (e.g., exploiting a technological efficiency improvement to preempt a rival for own exclusive use) or in a way that is accommodative toward competitors (e.g., sharing a resource or resulting benefits with them). We illustrate this concept based on a simple numerical model and develop propositions and insights about a firm's innovation deployment choices (e.g., exclusive competitive commercialization, cooperative licensing, sleep/delay, or some hybrid combination of these) and examine conditions when firms should compete aggressively to achieve exclusive benefit or cooperate in the commercialization and licensing of patented technology.

1.1 Review of Research

Early research on cooperation between competitors largely viewed this phenomenon as a form of collusion that restricts rivalry and thereby exploits market power (Porter and Fuller, 1986). However, the growing popularity of new forms of cooperative inter-firm relationships like licensing and cross-licensing agreements (Arora & Fosfuri, 2003; Fosfuri, 2006; Grindley & Teece, 1997), joint ventures (Chi, 2000; Harrigan, 1988; Kumar, 2005, 2011) and strategic alliances and networks (Gulati, 1998; Gulati, Nohria, & Zaheer, 2000; Kogut, 2000), has enticed researchers to consider a broader range of potential motivations beyond simple collusion. This emerging body of cooperation research has yielded a more comprehensive, balanced, and more nuanced understanding of collaboration goals (Lavie & Rosenkopf, 2006), partner selection (Beckman, Haunschild, & Phillips, 2004; Gulati, Lavie, & Singh, 2009), alliance management (Hoffmann, 2005, 2007), firm performance (Reuer & Koza, 2000; Zollo, Reuer, & Singh, 2002), and value appropriation (Gulati & Singh, 1998; Lavie, 2007).

Despite recent advancements, the rivalry-cooperation interplay remains under-researched (Chen & Miller, 2012, 2015). Specifically, most research on the interplay between cooperation and competition views it through a fairly static lens – i.e., as a phenomenon that exists in order to solve a problem occurring in a given period or situation. With only a few exceptions (e.g., Bengtsson & Kock, 1999; Luo, 2007; Rusko, 2011), coopetition research has largely neglected the question of how and why the relative balance of competition and cooperation may shift as circumstances change. One notable exception is theory suggesting that the leading firm in an industry prefers more aggressive competition when it enjoys a larger competitive advantage (Chatain & Zemsky, 2011; Makadok, 2010) – with limited indirect empirical support for this hypothesis (for a review, see Makadok, 2011: 1321-1322). Another notable exception is a study by Marx, Gans, and Hsu (2014) showing that disruptive innovations may motivate the innovator to switch from a competition to cooperation posture over time as the innovation becomes more accepted, while less disruptive innovations usually do not exhibit this dynamic shift.

One arena where researchers can most readily observe the competition/cooperation interplay is in the development and protection of intellectual property. In particular, we focus here on innovation deployment strategies. Strategic patent deployment extends the use of patents beyond the traditional exclusive (i.e., preemptive) exploitation of technology (Cohen, Nelson, & Walsh, 2000; Reitzig, 2004; Rivette & Kline, 2000; Somaya, 2012) to other potential uses that differ in the spectrum of competitiveness versus cooperativeness vis-à-vis rivals. These alternative uses include not only the conventional (i.e., cooperative) approach of licensing (Arora & Ceccagnoli, 2006) but also: (1) fighting defensively by building a patent wall around a core patent for strengthened protection, (2) fighting offensively by blocking a rival's patent, (3) aggressive litigation for purposes of securing monetary damages, (4) cooperation-motivated posturing for purposes of pressuring or forcing subsequent collaboration on a potential partner, or (5) cooperatively exchanging IP via cross-licensing, technology alliances, or patent pools.

The preemptive deployment of a patent intended to exclusively exploit a technology for a firm's own commercial use to enhance its competitive advantage, on one hand, improves the appropriability of returns to R&D for incumbents with strong market power (Ceccagnoli, 2009). Patent licensing, on the other hand, is viewed as a means of inter-firm cooperation and technology transfer. A firm's decision to license out to rivals is also influenced by imitation, first-mover advantages and transaction costs (Hill, 1992). The slower the diffusion of technology, the longer the innovator can exploit first-mover advantages by keeping the technology proprietary (Lieberman & Montgomery, 1988). But when rivals have strong incentives to imitate, licensing is more appealing to enable early standard-setting or rent appropriation via royalty payments and reduce damage from imitation. A firm's rate of technology licensing is driven by the degree of competition, market share and product differentiation (Fosfuri, 2006). Licensing out a patented technology foregoes the ability to preempt the rival, so it is advised only if innovation advantage is small or incremental. Licensing contract design deals with market imperfections, including market and technical uncertainties, appropriability, costs of technology transfer, agency and hold-up problems (Davis, 2008). Licensors pursue different strategies with contractual structures to address these challenges (Somaya, Kim, & Vonortas, 2011). Generally firms avoid licensing out patents in a proprietary strategy (Teece, 1986). In technology commercialization (TC), appropriability and complementary assets favor a cooperating strategy via licensing (Arora & Ceccagnoli, 2006), while size and prior market power restrain licensing (Gambardella, Giuri, & Luzzi, 2007). IP strategy has become "more proactive" (Grindley & Teece, 1997), with cross-licensing enabling "freedom-to-manufacture" against infringement (Teece, 2000).

In much of TC/IP strategy research (Gans & Stern, 2003; Teece, 1986), an innovative entrant's choice has been conceptualized as a static binary commitment: Depending on environmental, competitive and organizational factors, firms are assumed either to compete against incumbents in the product market or to cooperate with them permanently via licensing the technology. This binary commitment has led to the implication that disruptive technologies bring about the exit of incumbents (Christensen, 1997). However, this may not be the case if hybrid (i.e., switching) strategies are considered. Recently researchers have begun to appreciate the intricate and potentially beneficial interactions that may arise when firms choose to switch from competitive to cooperative strategies. For example, early-stage competition in the product market may help resolve uncertainty about the value of technology or otherwise establish credibility that may facilitate cooperation later on (Arora, Fosfuri, & Gambardella, 2001; Marx et al., 2014) or may also provide learning benefits (Gavetti & Rivkin, 2007), while conversely early-stage cooperation may enhance learning and knowledge/technology transfer that can strengthen a long-term competitive position (Hamel, 1991; Kale & Singh, 2007; Khanna, Gulati, & Nohria, 1998).

Marx et al. (2014) consider a two-stage commercialization strategy (TCS) for disruptive technologies involving a start-up innovator competing in the product market at first to establish the value of its technology and later switching to a cooperative strategy via licensing once the uncertainty is resolved or the incumbent's integration costs decline. This is a sequential across-time switch from competition to cooperation driven by two special characteristics of disruptive technologies: (i) uncertainty about the future value of the entrant's innovation (making the incumbent reluctant to cooperate at first) and (ii) initially high costs of integration with the incumbent's existing product line or infrastructure that decline over time (hence giving an incentive for the incumbent to wait-and-see). These are based on assumptions that the organizational effects of such innovations are competence-destroying (Tushman & Anderson, 1986) and that these technologies are initially less compatible, poorly-performing and costly to integrate, but that they improve over time (Christensen, 1997). The initial competition mode and later strategy switch to cooperation is driven critically by these features, and not by the uncertainty of the innovation or of market demand. The above drivers do not provide a justification for opposite-type switches – i.e., from collaboration to competition, which can be found in about 4-5% of the Marx et al. (2014) sample of speech recognition companies.

Our work complements their study by showing that flexible strategy (involving switching and adaptation) motives are broader (relating to the dilemma between commitment and flexibility and the tension of getting a bigger share of a smaller pie under rivalry vs. a smaller share of a bigger pie under cooperation under certain contingencies), and go beyond the above specific features of disruptive technologies. In our broader setup switches among competitive and collaborative modes can be bi-directional and can reverse as the level and volatility of demand shift. That is, while reduced technological uncertainty is a precondition that enhances the value of switching from competition to collaboration (only) in disruptive technologies, the role and impact of uncertainty here is different, with higher demand uncertainty favoring switching in either direction even for incremental (non-disruptive) innovation.

We aim to extend TC research on the competition-cooperation interplay, advocating a more flexible notion of strategic IP deployment involving a menu of flexible innovation (patent) strategies enabling the firm to switch among compete, cooperate or wait (patent sleep) modes. We examine the optimality of different innovation strategies based on demand, market uncertainty, industry dynamism, and the radicalness of the innovation – without adopting the specific assumptions of "disruptive" innovation (Christensen, 1997). In this way, we identify circumstances where strategic patenting is best used to compete, such as defending oneself by building a patent wall around one's core patent or go on attack bracketing the rival's patent, or to cooperate via licensing out or cross-licensing one's patented technologies. Whether firms compete or cooperate depends on firm-specific, competitive, and environmental contingencies. A flexible innovation strategy allows switching from one competitive posture to another, such as switching from competition to cooperation or vice versa, in response to changes in demand, market volatility, or the magnitude of the innovation advantage. We show that the assumptions of "disruptive" innovation relied on by Marx et al. (2014) are not needed for deriving switching strategies in the IP deployment context (but uncertainty is). We abstract away from motives such as the need to prove the technology or assumptions of facing high upfront and later declining integration costs, focusing instead on the role of the level and the uncertainty in demand. Our framework thus helps extend understanding of flexible or hybrid pivot strategies by expounding more general conditions when is best to compete or to cooperate, or to switch from one to another, and provides guidance on how to flexibly use IP as a general strategy tool.

A question that arises then is: Under what conditions might one expect such a flexible strategy to be valuable? We argue that the chosen strategy depends on contingency factors such as the degree of innovation (incremental or radical) and the level and volatility of market demand. We focus on the context of strategic deployment of patents as this allows the competition or cooperation mode to be chosen endogenously, depending on these contingency factors, while also accounting for competitive interactions. These patent deployment strategies may involve different choices (switching) across time periods or across demand conditions. We focus on the tension between strategic use of patents to strengthen one's position to exploit more of the technology space for own exclusive advantage (e.g., via costly offensive bracketing of the rival's patent in high demand or raising a defensive patent wall around one's own patent in medium demand) in pursuit of exclusionary asymmetric profits vs. the symmetric collaboration benefits of sharing a larger market pie involving collusive-type (monopolistic) rents.

In particular, we argue that in case of large or radical innovation in high demand states the innovator might be better off to accept a smaller share of a larger market pie rather than aim for a bigger share of a smaller pie resulting from higher bracketing costs and an ensuing price war. More generally, we revisit the notion of flexible business strategy within the context of strategic patents deployment to incorporate endogenous strategic interactions, emphasizing how path-dependent asset accumulation (Dierickx & Cool, 1989) requires not only tradeoffs between commitment and flexibility under uncertainty but also shifts between competing and cooperative strategy modes. Our approach thus complements the resource-based view (RBV) and dynamic capabilities (Teece, Pisano, & Shuen, 1997) to also account for strategic interactions and flexible innovation strategies.

Another related study on patenting strategies by Mihm, Sting, & Wang (2015) examines how firms manage the tradeoff between patent protection versus knowledge leakage from patent application disclosures. Using a simulation, the authors examine how business environment and firm contingencies affect the strategy whether to patent or not. By contrast, we consider a situation where a patent already exists and then analyze how different firm-specific, competitive, and environmental contingencies affect how to use that patent strategically, focusing on a different tension: whether to commit resources and compete aggressively to dominate the market or to share in a flexible collaborative manner a potentially larger market pie. Although these two questions – whether or not to patent in the first place, and how to deploy an existing patent strategically – may at first seem similar in terms of the motives and contingencies involved (e.g., protection, defensive/offensive blockade and exchange motives or competitive behavior/strategic interaction contingency), they can also be quite different.

1.2 A Flexible Innovation (Patent) Framework

By flexible innovation (patent deployment) here we mean a firm's complete set of choices about which exercise mode it chooses in each time period. The alternative exercise modes have different implications for the type and intensity of market rivalry. We assume that all firms are practicing entities that profit from serving customers in a market. We allow for patent deployment strategies to be flexible in having the ability of switching among exercise modes (e.g., competing through exclusionary commercialization, cooperating through licensing, waiting, or exiting) under different contingent circumstances, such as: (1) future level of demand, (2) demand volatility, (3) industry dynamics, and (4) the relative advantage of the new innovation controlled via a new patent by innovator firm A – i.e., whether it is radical or incremental compared to the old technology already exploited via an existing patent by incumbent rival firm B. Besides strategic patent use motives (e.g., preemption, blockade, or rivalry restraint), we abstract away from other motives such as the need to prove the value of the technology or facing high upfront and later declining integration costs.

We consider three outcomes (types) of an entrant's patented process innovation resulting in either no, small (incremental), or large (radical) cost advantage, and examine a situation where two patent-holding firms, entrant firm A and incumbent firm B, are involved in a two-stage strategic patent deployment game. The timing of the game is as follows:

I. At time 0 (beginning of stage I), entrant firm A acquires a patent on new core technology (resulting from earlier innovative activity) that may be superior to the existing technology held by incumbent firm B. We suppose the two firms are of equal market power (prior to the new patent by firm A) so firm A potentially gets an asymmetric advantage over B.
II. At time 2 (after two subperiods resulting in three demand states, at beginning of stage II), each firm makes a decision on its best innovation strategy vis-à-vis its rival (competing through exclusionary commercialization, cooperating through licensing, waiting, or exiting), depending on firm A's relative innovation advantage and the state of industry demand (High, Medium or Low).

New entrant firm A can extract significant value if its innovative process is protected effectively by a superior patent relative to incumbent firm B´s existing technology. For convenience, assume no uncertainty about the value of the new technology and perfect legal protection. Firm A´s patent is a legal resource converting its R&D activity into a proprietary investment giving it distinct technological advantages over its rival. Given demand uncertainty, if market demand is favorable the firm has valuable flexibility to exploit the new patented technology on its own by making a technology commercialization investment (I = \$80 m). At time 2, either firm may use its respective patent in a strategic way. It may follow a defensive patent strategy (e.g., building a patent wall around its own core patent) or engage in an offensive fight with its rival ("bracketing" each other´s core patents). If demand is highly uncertain or demand conditions are currently not favorable, firm A either may wait and keep its patent "sleeping" or may pursue a cooperative cross-licensing patent strategy until reconsidering the situation in the next period.

The situation is more complicated when there is significant market demand uncertainty under rivalry. If entrant firm A faces an incumbent firm B with an old technology in the same product market, each firm's innovation strategy may also depend on its rivals' patent-deployment moves. When the competitive setting involves such strategic uncertainties, firms may be better off to flexibly exploit patents as strategic deployment options. When competition is endogenous, a game-theoretic treatment is required. Firm A must consider both how its investment decision affects its rival and how it may be impacted by rival reactions. A number of issues are addressed: What type of innovation strategy (e.g., cooperative or competing) should firm A pursue (in stage II) depending on its relative innovation advantage (determined by the strength of its own innovation), the state and volatility of demand and the nature of competition? Should it compete to exploit innovation advantages for its own exclusive use or should it share them with its rival? Should the strategy change in different circumstances and if so, how?

If the firm follows a standard DCF approach to valuing the patent, its static value is obtained by discounting its expected future cash flows (net of investment outlay, I, of $80 m) back to the current time (t = 0) using the cost of capital (assumed k = 20%). Expectations are taken by assigning appropriate probabilities to the occurrence of each scenario at the end of period 2. The static NPV of the patent, assuming immediate investing, is estimated at $20m (= V – I = 100 – 80). This analysis ignores the dynamics and options resulting from the second-stage patent deployment game among the two firms. A summary of key assumptions and input parameters for the valuation is given in Figure 1.

The patent will have higher value if recognized that it can be strategically used either against or for the benefit of the competitor. This involves ascertaining the degree of technological advantage (radical or incremental) and the nature of competition in the industry, accounting for rivals' strategic moves under different demand realizations. Assuming rationality of players in strategic interaction permits deriving each player´s payoff values in industry equilibrium. In selecting one of the patent strategies, firm A must account for the type of innovation (incremental or radical), the market power of the incumbent and the state and volatility of demand (e.g., low, medium or high). The same applies to firm B. Each firm decides which strategic move to make. Different combinations of the above factors produce different types of industry equilibria. Several equilibrium innovation (patent deployment) strategies may result involving different exercise modes depending on demand (high, medium or low) and the size of technological innovation advantage (no, small/incremental, large/radical).

The combination of three states of demand (after two subperiods) for each of three relative technological size advantage scenarios results in 9 subgames, each potentially involving different equilibria and optimal patent deployment strategies, as summarized in Figure 2. If there is no significant innovation cost advantage resulting from firm A’s patented innovation and the firms are otherwise a priori symmetric in market power, they are more likely to cooperate by cross-licensing their patents to each other. At the other end, if firm A’s innovation brings about a large (radical) advantage, the competitive mode is more likely. The precise strategy depends on the level of demand, with high demand potentially involving more offensive strategies (e.g., bracketing), intermediate demand involving raising a defensive patent wall by the firm with the stronger patent (or by both against third entrants) to reinforce their advantage and potentially drive the rival(s) out, while in low demand letting the patent sleep by simply waiting.

The two patent holders compete in the same industry as a duopoly behaving rationally. Each pursues a deployment strategy (from time 2 onward), resulting in a given value payoff. Patent deployment choices during stage II take the generic form “sleep” (wait-and-see) versus “invest.” Investing under a cooperative mode involves licensing-out one’s patent to the rival or cross-licensing patents (both firms invest). One or both firms may let their patent sleep. Keeping one’s patent sleeping amounts to deferring the decision to license or commercialize until next period. Holding a sleeping patent is a wait-and-see option. This option is more valuable when demand is volatile. Letting the patent sleep results in a specific continuation (or call option) value (C). In such a wait-and-see strategy, if both firms let their patents sleep a stronger patent position for firm A allows it to appropriate a larger share (s %) of total continuation value (i.e., sC). Firm B would capture the remaining, smaller portion, (1 – s)C. In general, the driving force of the sharing terms of end-of-period collaboration between the firms is the relative market power based on the cost advantage or size of innovation of firm A´s patent relative to firm B´s. If firm A’s innovation is large (radical), firm A appropriates most of NPV or C; if small (incremental), firm A gets a lesser %. If there is no cost advantage from the patent, market value sharing is 50-50. The continuation value represents an option on stage II-total market value (V).

Under the competitive choice, investing involves either a defensive patent clustering strategy via a patent wall around one’s core patent (to keep the opponent out) or each firm pursuing an offensive patent bracketing strategy to block its opponent from exploiting its patent (both firms invest). The implementation cost (similar to the exercise price of a call option) is the base commercialization cost, though it may be delayed, increased or reduced depending on strategy choice (sleep, compete or collaborate). Cooperation via licensing is assumed to result in an enlarged market value pie. By contrast, a fighting mode would result in a reduced market value pie due to ensuing costly patent wars. These changes to the size of the industry or market pie are captured by an exercise mode multiplier (m), amplifying the underlying market value to mV. On the other hand, in the case of fighting, f (<1), so mV = fV < V. As noted, one or both firms may let their patents sleep instead of investing. If both firms postpone a fight, the continuation value refers to the next-period equilibrium in which firms A and B receive a declining market value because of intensified rivalry. Each firm´s payoff corresponds to the present value of expected future cash inflows generated by its specific patent strategy. An options game valuation of firm A's patent deployment strategy depends on the equilibrium solution found for each of the investment subgames composing the overall options game. The equilibrium outcome values in High, Medium and Low demand constitute the payoffs in the end-of-period nodes (in a binomial option tree). These are weighted by the respective (risk-adjusted) probabilities and discounted back at the riskless rate (r). Firms choose their respective patent deployment strategies simultaneously.

1.3 Main Findings

Several interesting results are obtained depending on the level of demand and the degree of innovation advantage. First, when a pioneer firm's innovation is radical, competition is more likely. The precise innovation strategy may differ across demand regimes. It may range from offensive fighting (e.g., bracketing the opponent's patent) in high demand or dynamic industries, to defensive fighting (e.g., building a patent wall) by the advantaged firm to drive out its rival in intermediate demand, to a wait-and-see strategy with an option on future exclusionary monopoly profits in low demand.

Second, in case of incremental (small) innovation advantage, the firm may be better off to pursue a flexible strategy allowing switching from a competitive exercise mode (e.g., bracketing the rival's patent) at high demand to a cooperative exercise mode (licensing) at lower/medium demand levels. The circumstances around the above finding involving flexible innovation strategies are particularly interesting as they give rise to pivoting from competition to cooperation under incremental innovation simply as a result of shifts in market demand or volatility conditions, without relying on the specific assumptions of sequential (staged) resolution of uncertainty about the value of the technology and gradual decline in the costs of technology integration that characterize disruptive technologies (Marx et al., 2014). In the latter setup firms pay a cost to resolve the uncertainty of the technology, which is assumed to decline over time for disruptive technologies. We assume away uncertainty in the value of the technology and the cost of its integration and instead focus on uncertainty in industry demand. As a result, in this setup the above flexible strategy switching can be in the reverse (i.e., from a cooperative to a competitive exercise mode) if demand or volatility shifts are opposite, something that is not explainable under the disruptive innovation theory. Whereas in Marx et al. (2014) firms start by competing in the market entry stage and switch over time across stages as the uncertainty of the technology or the cost of its adoption decline, switches in our setup can occur contemporaneously across demand states and the value of switching increases with industry demand uncertainty. That is, whereas in the disruptive innovation setup reduced technological uncertainty is a precondition that enhances the value of switching from competition to collaboration (only), in our setup higher demand uncertainty favors flexible strategy switching in either direction even for incremental (non-disruptive) innovation, with the role and impact of uncertainty being opposite.

A strategic patent investment thus can be seen to involve a portfolio of patent options (e.g., to exit, sleep, license in or out, cross-license, cooperate through raising a patent wall or a bracketing war). Each of these options has the base economic value of the commercialized patent as underlying asset. The resulting equilibrium payoffs in each state of demand for a given technological or competitive advantage (No, Small or Large) are then weighted by their respective (risk-adjusted) probabilities and discounted back to the present (at the riskless interest rate r within a backward binomial option valuation process).

In case of large or radical innovation, firm A might recognize that in high demand (H) it might be better off to cooperate (e.g., via cross-licensing), obtaining a smaller (½) share of a larger market rather than fight offensively shouldering higher bracketing costs to obtain a higher share of a fiercely contested and consequently smaller pie. Such a flexible innovation strategy, switching from a compete mode via raising a defensive patent wall to strengthen its patent advantage in medium demand (with room for just one firm) to a cooperative relationship via cross-licensing in high demand, might result in a higher Strategic NPV (S-NPV). This flexible strategy under radical innovation can be more valuable than the cooperative strategy under no advantage involving symmetric firms or the flexible strategy under small innovation advantage. Figure 3 illustrates how the value of the patent strategy (S-NPV) varies with the degree of innovation advantage (asymmetry) measured by the market concentration (Herfindahl-Hirschman Index or HHI) at different levels of volatility (σ) under the compete, cooperate, and flexible or hybrid strategies. The cooperation and flexible strategies are at a higher (elevated) value level.

We next consider alternative specifications by extending the baseline model. We first examine the tradeoff between competitive and cooperative modes for high demand and extend our investigation considering a broader menu of flexible deployment strategies at more extreme levels of demand or involving higher volatility in dynamic industries, highlighting the value of flexible strategies allowing to switch among various compete, cooperate, sleep or exit modes. Figure 4 highlights the tradeoff between the cooperate vs. compete strategies arising in high demand states in case of radical innovation examining the sensitivity of Strategic NPV to the cooperation multiple ($m = c$). It shows the sensitivity of S-NPV to cooperation multiple (c) assuming large innovation advantage under a cooperate/hybrid strategy. For $f^* = 0.96$ cooperation is beneficial when the cooperation multiple exceeds $c^* = 1.2$. Figure 5A extends the sensitivity analysis of S-NPV to the cooperation multiple (c) under different innovation advantage cases. Even under a large technological advantage, a rigid fight strategy results in lower value. Above a cutoff level of 1.1, having a small advantage under a flexible innovation strategy is preferable to a rigid fight strategy, as collaboration via (cross) licensing in the low and medium states enhances value. Below a cutoff level ($c = 1.17$), having a small advantage results in a higher value than having no advantage, but at a higher cooperation multiple no advantage might lead to higher value as it induces cross-licensing in all demand scenarios whereas under small advantage a fight bracketing strategy may ensue in the high demand regime (as in Figure 2). A flexible cooperation strategy under large advantage here seems best.

Figure 5B presents sensitivity of Strategic NPV to volatility (σ) under no, small and large innovation advantage. The conflict between competition and cooperation in high demand states leads to the value discontinuity or gap between the rigid fight strategy and the flexible switch (cooperative) strategy S-NPVs under radical innovation. S-NPV values decline at lower volatility levels as expected. An interesting discontinuity in the S-NPV values is observed around a critical volatility level (of about $\sigma^* = 38\%$). This discontinuity arises due to a shift in certain equilibrium subgames as volatility declines below a critical threshold level. Under radical innovation, in low demand the equilibrium strategy is to sleep (wait) under high volatility; but as σ declines below σ*, the value of the wait-and-see option declines, while the attractiveness for the advantaged firm to fight and drive the weaker rival out given low demand and low recovery prospects rises. But at very high demand, cooperation is attractive under high volatility in dynamic industries, partly deriving from the option to jointly appropriate the value of open innovation and optimizing future decisions under demand uncertainty, avoiding the prisoner´s-type dilemma of both firms investing prematurely under the pressure of competitive rivalry. As volatility declines below a certain level, however, there is a switch from cooperative to competitive equilibrium involving a shift from the wait (sleep) mode to a rigid fight mode. Figure 6A shows, in case of large innovation advantage, that at low volatility (σ) a rigid, fight-only strategy (e.g., raising a defensive patent wall to strengthen the patent´s large advantage) may be best. However, as the cone of uncertainty rises a wider menu of strategic choices opens up, including sleep/exit at the low end and cooperation at high (as well as middle) demand. At high volatility (σ = 90%), optimal patent deployment strategies span the whole range from exit, sleep, defensive fighting (raising patent wall), offensive competition (bracketing), and cooperation (cross-licensing).

Figure 6B provides an overview and an extension (including the case of small and no advantage) of the various cooperate vs. compete patent strategies that may be optimal when a broader range of demand states is possible under highly volatile markets. The case of large (radical) innovation (rightmost column) corresponds to the high volatility case (rightmost column) of Figure 6A above. Here, higher demand volatility allows adding Very High (VH) and Very Low (VL) demand states at the two extremes after an additional time period. As previously, in determining the equilibria for each of the various cooperate or compete subgames, the firm would select the type of patent strategy S (e.g., sleep or exit, licensing out, cross-licensing, raising patent wall, or bracketing) and associated options to optimally exercise depending on different market demand (or volatility) conditions and the size of its technological advantage. The optimal patent strategy is a function of the size of competitive/innovation advantage C (No, Small, Large), the cooperative or competitive strategy mode m (cooperate, c, or fight, f), and demand level regime D (e.g., VH, H, M, L or VL). Under large technological advantage (L) strategic patent deployment by firm A may span the entire menu of available options depending on prevailing market demand conditions: abandon or exit when demand is very low (VL); sleep or "wait and see" when demand is low (L); expand/strengthen the innovation through a patent wall to preempt the rival and gain monopoly position at medium demand (M), while at times cooperate with the rival to preempt third entrants;

engage in offensive fighting via bracketing in high demand (H); and potentially switch to a cooperative mode (cross-licensing) at very high levels of demand (VH), allowing room for both.

In general, under radical innovation, the optimal deployment of an innovative firm may vary or switch among defer or exit, and compete or cooperate, depending on the level of demand and other conditions such as volatility and industry dynamism. Under volatile conditions, deployment should beflexible, able to adapt and switch among various compete, cooperate or sleep modes. Patent-driven innovation strategy is generally hybrid when the innovation advantage is marginal, with small variations in demand, e.g., from High to Medium, necessitating a strategy switch from a compete mode (e.g., bracketing) to a cooperate mode (licensing). This may also be the case when innovation is radical, with cooperation possibly prevailing unless the market is limited. These flexible strategy switches among cooperate, compete or sleep modes bring about value discontinuities and non-trivial tradeoffs not fully recognized in traditional analyses. The above insights can be summarized in the following.

Cooperation via licensing can prevail in volatile regimes, even when innovation is radical, under high demand when the (smaller) share of joint benefits exceeds the dominant share of a reduced market pie from a costly patent war. At high demand, initially give-up strategies may switch to competition and then, at higher demand in volatile regimes, to cooperation. Volatility exacerbates these switch patterns between competition and collaboration. That is, even with a superior innovation, a start-up or entrant should still consider the full menu of compete and cooperate strategies, potentially switching among sleep, compete and collaborate modes as demand changes in pursuit of a dynamic competitive strategy.

1.4 Discussion/Contribution and Implications

At its core, business strategy is fundamentally about making trade-offs (Porter, 1996). Perhaps the two most consequential strategic trade-offs that firms must make are competition versus cooperation (Brandenburger & Nalebuff, 1996) and flexibility versus commitment (Ghemawat & del Sol, 1998). While much research has focused on understanding these two trade-offs in isolation from each other, researchers have devoted relatively little attention to the issue of how they interact. This analysis offers a framework for integrating these two types of trade-offs. We focused on the innovation context of strategic deployment of patents in “proactive” business strategy (Cohen et al., 2000; Grindley & Teece, 1997; Reitzig, 2004; Somaya, 2012). This approach offers a possible interpretation of the finding of Lado, Boyd, & Hanlon (1997) that successful firms "possess enhanced strategic flexibility by either holding or striking a wide variety of strategic options." It also offers a possible solution to a key research problem identified by Somaya (2012): "it would be valuable to incorporate the strategies and actions of rival and partner firms … actions initiated by rival firms may lead to competitive dynamics that have yet to be systematically investigated… it would be worthwhile to explore when firms are and are not better off pursuing 'weak,' nonproprietary [collaborative] patent strategies to enhance the value creation potential of their innovation."

Our work extends recent contributions using real options in technology and strategy (e.g., McGrath & Nerkar, 2004; Oriani & Sobrero, 2008), especially those with a game theoretic perspective (Camerer, 2007; Ferreira et al., 2009), by illustrating how a flexible innovation strategy can be formulated. Our results suggest that the optimal innovation strategy is moderated not only by the strength of the innovation advantage, in line with extant licensing literatures (e.g., Somaya, 2012), but also by the level and volatility of demand. We also extend related literature on strategic alliances (Arend & Seale, 2005; Chi, 2000; Gulati, 1998; Kogut, 1991; Somaya et al., 2011; Teece, 1986) and licensing strategies (Anand & Khanna, 2000; Davis, 2008; Fosfuri, 2006) by analyzing the contingencies when firms should collaborate or compete in redeploying their IP assets strategically under uncertainty.

This framework offers a dynamic approach to strategy under competition. In the context of innovation or patent deployment choices, this flexible approach to innovation policy greatly broadens the menu of possible IP strategies by enabling the firm to switch among compete (fight), cooperate, or wait (patent sleep) modes that may prevail under different future demand or volatility scenarios, under different magnitudes of innovation advantage, consistent with extant literature (e.g., Arrow, 1962; Ceccagnoli, 2009; Fosfuri, 2006). We confirm that radical innovation generally increases the benefit (and lowers the critical demand threshold at which it pays) to fight to attain proprietary or exclusionary benefits. The greater the advantage of the newly patented over the existing technology, the greater are the incentives to compete aggressively, e.g., by bracketing each other's patents or erecting a defensive patent wall (e.g., Nestlé's coffee machine Nespresso). This is analogous to the classic result in the licensing literature (e.g., Arrow, 1962; Hill, 1992) that drastic innovation should be kept proprietary, while patented technologies with incremental advantage might be shared via licensing out to capture royalty fees or as a defense against imitation. However, by moving beyond the known opportunistic factors, competitive forces and strength of patented innovation advantage, we complement existing research by uncovering important strategic drivers such as interactions among industry players and the role of market uncertainty, showing that existing results are moderated by such factors as the level and volatility of demand. We find that flexible innovation strategies seem to be well-ordered for small innovation advantage at increasing levels of demand, with competing aggressively becoming more attractive when demand gets higher (e.g., Yamaha and Bombardier's patent bracketing war), whereas collaboration is preferred in low or moderate demand (as in Genentech's licensing with Eli Lilly).

The dilemma between competition and collaboration in high demand regimes requires special attention as it may lead to value discontinuities and tradeoffs in dynamic industries. Radical innovation under moderate or high demand often induces a compete mode (e.g., via patent wall or bracketing strategies), in line with first-mover advantage motives (Lieberman & Montgomery, 1988). But our rationale here is distinct from and complementary to Hill's (1992) preference for licensing out to prevent imitation. It confirms and complements Hill's (1997) intuition that in an unpredictable and dynamic environment, a firm seeking to establish its new technology as an industry standard should switch between pure competitive (e.g., sole provider) strategies, assertive cooperation stances with sequential rival preemption (aggressive multiple licensing) and more sit-back collaboration strategies, depending on rival technologies, barriers to imitation and availability of internal complementary resources.

Our option-based framework is complementary to property rights theory (Anand & Khanna, 2000) suggesting that firms should avoid licensing a superior technology to reduce the risk of imitation. We give more weight to the benefits of collaboration in enhancing the value of the relevant market by fostering exchange of technologies and encouraging industry innovation. Such collaboration benefits may be lost when taking an aggressive stance that erodes market value. Aggressive competition may be justified in some cases, however, when the firm has a radical advantage, in line with Arrow (1962) and Hill (1992). But this holds if the market value erosion from fighting is limited or market demand is constrained enabling the firm with radical technology to drive the rival out and gain a monopoly position (e.g., Gillette Sensor's patent wall). Our preemptive innovation strategies under moderate demand and the moderating role of market power asymmetry are consistent with Fosfuri (2006) and Ceccagnoli (2009). A different strategy, however, may be appropriate if demand or the rewards of competing aggressively are so high that the rival may not be driven out and causes substantial damage fighting back. A careful scanning of rival behavior is warranted. Our analysis also enriches Davis (2008) in providing a more dynamic analysis of IP licensing strategies. This may enable licensing parties to negotiate better contracts adjusted in a contingent manner.

Our findings also support Chen's (1996) competitor analysis based on firm-specific factors. The collaboration strategy under no innovation advantage corresponds to Chen's (1996) high market commonality and resource similarity reducing the chance of attacking due to high-risk multi-market overlap and capability for retaliation. The compete strategy under radical innovation represents relationships in which inter-firm discrepancy in market focus and resource endowments is so strong that the firm is better off initiating a challenge. Our view also enriches Chen and Miller (2015) by accounting not only for a competitive but also for a cooperative stance among firms. Our main results are consistent with the findings of Marx et al. (2014) on pivoting strategies and the practical entrepreneurial practices in Ries (2011), whereby startups are encouraged to introduce a minimum viable product to obtain customer feedback to decide whether to persevere or switch. This reveals a richer set of situations under which firms should compete or cooperate in using their IP assets, enriching our understanding of patent strategy and IP management (Somaya, 2012).

In terms of implications for future research, this high-demand result may also help explain why, contrary to traditional prescription, cooperative approaches to commercializing a radical innovation might prevail in dynamic environments that entertain the prospect of very high levels of demand. This novel result merits further consideration and additional research. Our analysis suggests that if the firm follows a cooperating strategy (e.g., via cross-licensing of patents with rivals) it might significantly enlarge its strategic innovation value share by enlarging the industry pie. The joint benefits from cooperation enlarging the market pie may exceed the value from a higher share of a smaller market pie from winning an aggressive competitive battle net of higher fight costs. Under high demand one can also anticipate scenarios where there is fierce fighting to take advantage of exclusionary monopoly rents (a typical Microsoft stance), as well as other scenarios where collaboration might occur (e.g., via cross licensing) to jointly appropriate the value of open innovation and exploit larger joint rents, as in Intel and AMD's cross-licensing agreement. This complements Teece (2000). Under specific circumstances, collaboration may also prevail at moderate demand if incumbent firms fear competition from new entrants. Cross-licensing may raise a wall protection around incumbent oligopolists (e.g., IBM and Dell's cross-licensing agreement). Radical innovation may induce patent sleeping or rival exit under very low demand, as in EVT's selloff of its sleeping patented coronary stent technology to Guidant.

This analysis also reveals severe limitations of traditional NPV that treats the size of the market pie as given. In option-games analysis, firm decisions are contingent on both market demand and the incorporation of rival reactions into one's strategic patent moves. The size (and sharing) of the market pie is a function of the (competing, cooperating or hybrid) strategies pursued by the firm and its rivals, moderated by the demand level and volatility. When a firm pursues a compete strategy this may potentially lead to lower overall value due to ensuing aggressive competitive fights even when it has considerable innovation advantage. In such a case the strategic net present value of the patent strategy may be lower. Hence, the value of a patent strategy may be enhanced by a combination of favorable market conditions and via a cooperating stance (e.g., cross-licensing of patents) under high demand and volatility. Even in low demand with an incremental innovation advantage, the value of the associated patent strategy may be enhanced via licensing in anticipation of future collaboration.

Market or economic uncertainty can be value-enhancing as it not only increases growth option value but it also induces firms to pursue a flexible innovation strategy that allows to switch to collaboration as it reduces the likelihood and incentive of prevailing over a rival. This hidden potential from higher market uncertainty in dynamic industries can be exploited through a richer menu of strategic choices by cooperating firms. This is generally the case when firms are roughly symmetric with equivalent technologies (e.g., Google and Samsung). This is consistent with Fosfuri (2006), though for different reasons. If the innovator holds a marginal patent advantage, Fosfuri (2006) argues the incentive to license is low as there is low profit dissipation. We find that licensing out may be justified even under low or medium demand. Also, we find upside potential from collaboration may hold under very high demand or volatility conditions even when firms are asymmetric, as initially give-up strategies may switch to fighting and then, at higher demand, to cooperation. Flexible hybrid strategies may thus result, involving switching from one type of compete mode to another or from competition to cooperation as demand rises or as the patent advantage gets smaller. Volatility exacerbates and brings out these peculiar switching patterns between competition and collaboration modes. This is particularly relevant in emerging or dynamic technology industries characterized by change (Ang, 2008). Additional research is needed to test these predictions and better understand their boundary conditions.

2 Impact of Market Uncertainty on Economic Outputs and Policy

In this part we address the role of uncertainty in economic forecasts and policy making, specifically examining the impact of macroeconomic uncertainty on U.S. real economic activity based on U.S. data during the period 1990-2014. We confirm that market uncertainty tends to depress production, consumption, employment and aggregate economic output in line with real options and other economic theory predictions.

2.1 Review of Research

Various economists have examined the impact of economic uncertainty and macroeconomic shocks on economic activity and their persistence in the real economy (e.g., Bloom, 2009; Caggiano et al., 2014; Leduc & Liu, 2016). The overall evidence suggests a negative effect of uncertainty and volatility shocks on economic output (e.g., Fernández-Villaverde et al., 2011; Christiano et al., 2014). A few papers have been devoted to the study of Knightian uncertainty, as considered by Knight (1921) and Ellsberg (1961), and its association with real economic activity. Jurado et al. (2015) document a negative relationship between forecast errors and real economic activity. Based on international indexes of economic uncertainty using surprises from economic announcements, Scotti (2016) finds a mild impact of economic uncertainty on real economic activity, mostly employment. We here examine the impact of extreme market uncertainty on real economic activity in a more comprehensive manner using uncertainty information elicited from the financial markets.

Prominent economic theories advocate that uncertainty will have adverse effects on real economic activity. Real options (along woth financial frictions and precautionary savings) point to a negative association between uncertainty and broader economic performance (i.e., investment, production, consumption and employment) (Trigeorgis, 1996; Kimball, 1990; Guiso, Jappelli & Terlizzese, 1992; Hall, 2010). This adverse impact on real economic indicators should be more pronounced when Knightian uncertainty rises in the economy and the financial markets (e.g., Nishimura & Ozaki, 2007; Baker et al., 2016).

In thissection, we exploit linkages between the financial markets and the real economy to show how option market-elicited uncertainty could have adverse lasting effects on real economic activity in the U.S. Our data covers the period 1990 to 2014. We elicit our uncertainty measure from the financial options market, an environment that reflects investors' aggregate expectations about future market outcomes. We then test in a VAR system, using a number of statistical prediction procedures, the extent to which market uncertainty is reflected in various aspects of real economic activity. Since we employ a market-based measure of uncertainty, we benchmark our findings against those of other prominent market-based predictors from the financial economics literature. We show that our market-elicited uncertainty measure is negatively associated with each key aspect of economic activity (production, employment, consumption, and overall economic output), confirming predictions from real options and extant economic theory. Our results are robust and have incremental predictive ability after controlling for risk aversion and alternative financial uncertainty proxies. Our uncertainty measure inferred from the financial markets correlates well with a number of known (macro)economic uncertainty proxies. These include statistical-based and survey/media-coverage measures (e.g., conditional variance of industrial production growth; macroeconomic uncertainty indicator of Jurado, Ludvigson & Ng (2015), and the surprise and uncertainty indices of Scotti (2016)). We thus provide novel and more comprehensive evidence that uncertainty in the financial markets matters in real economy forecasts and that it complements prevalent economic uncertainty predictors.

2.2 Measuring Market Uncertainty

We elicit investors' extreme uncertainty preferences from option market prices based on the rank-dependent expected utility framework of Chateauneuf, Kast, & Lapied (1996) and Chateauneuf, Eichberger, & Grant (2007) using Choquet Brownian motions (see also Hong & Karni (1994), Kast & Lapied, 2010 and Gul & Pesendorfer (2014)). This approach was extended to option pricing by Driouchi, Trigeorgis & So (2016) and has been used to examine corporate financing decisions under extreme uncertainty by Agliardi, Agliardi & Spanjers (2016). The underlying asset (market index) process under Choquet-type uncertainty is assumed to be:

$$\frac{dS}{S} = (\mu + m\sigma)dt + s\sigma dz \quad (\forall m \in]-1,1[, \forall s \in]0,1]) \tag{1}$$

where S is the set of possible prices for the underlying asset (here the S&P 500 stock index) with a range of mean drifts $\mu + m\sigma$ and standard deviations $s\sigma$ per unit time. Capturing miscalibration and parametric uncertainty in the mean and the variance of Eq. (1), m and s are the mean and standard deviation of a general Wiener process W following $dW = mdt + sdz$, with z being a standard Wiener process.

Parameters mσ and s entertain (multiple states of) extreme uncertainty in the mean and variance of the process; these are functions of capacity score c, with 0 < c < 1. The situation c < 0.5 indicates investor extreme uncertainty aversion, c = 0.5 is risk neutrality, and c > 0.5 suggests extreme uncertainty-seeking (see e.g., Kast & Lapied, 2010; Agliardi et al., 2016). Under this more general Brownian motion, the distance of capacity c from the risk neutral value of 0.5 is indicative of the degree of aversion to extreme uncertainty characterizing the representative market investor (Kast et al., 2014; Agliardi et al., 2016). This relates to Abdellaoui et al.'s (2011 approach to eliciting pessimism using source functions. Based on the Choquet framework of Eq. (1), the price of a European call option 'adjusted' for extreme uncertainty (A-OPM) takes the form (see e.g., Driouchi et al., 2016; Agliardi et al., 2016):

$$C_t^A = S_t e^{-\delta' T} N(d_1') - K e^{-r' T} N(d_2') \tag{2}$$

where

$$d_1' = \frac{\ln\left(\frac{S_t}{K}\right) + \left(r' - \delta' + 0.5(s\sigma)^2\right)T}{s\sigma\sqrt{T}}; \; d_2' = d_1' - (s\sigma)\sqrt{T} \tag{3}$$

$$r' = r + m\frac{[r - (\mu + m\sigma)]}{s^2\sigma}; \; \delta' = \delta - \frac{(m + s^2\sigma - s\sigma)[(\mu + m\sigma) - r]}{s^2\sigma} \tag{4}$$

$$m = 2c - 1 \; and \; s = \sqrt{4c(1-c)} \qquad (\forall c \in]0,1[) \tag{5}$$

In Eq. (2), C_t^A is the price of a European call option under extreme uncertainty at time t, S_t is the current market price of the underlying asset (the S&P500 here), K is the strike (exercise) price, σ is return volatility, δ is any form of 'dividend yield', and T is time to maturity. Variables r' and δ' in Eq. (3) are the subjective discount rate and subjective dividend yield, respectively. They are contaminated by m and s. These behavioral variables summarize uncertainty in model parameters and capture (through capacity score c) economic agents' model misspecification (miscalibration) under extreme uncertainty (Sarin & Wakker, 1992; Hong & Karni, 1994; Ghirardato & Marinacci, 2002; Chateauneuf, Eichberger, & Grant, 2007). Along with disagreement in beliefs, miscalibration can distort economic and financial fundamentals through confusion, fear and erratic trading behavior, leading to lower investment, production, hiring and consumption (Baker et al., 2016). When c = 0.5 (risk neutrality), m = 0 and s = 1, Eq. (2) reduces to the standard Black-Scholes option pricing model (OPM) (adjusted for constant dividend yield δ).

For data quality and comparability purposes, we use the price of CBOE's volatility index (VIX) as an input to our extreme uncertainty 'adjusted' option pricing model (A-OPM) of Eqs. (2-4) to elicit uncertainty information from the options market. This approach is analogous to Jiang & Tian (2005) in a curve-fitting exercise for computing model-free implied volatility, and to Cremers & Weinbaum (2010) in calculating put-call parity for return prediction. Our results are unchanged if we use option prices, rather than VIX, as inputs in our elicitation of the uncertainty c measure.

By inverting Eq. (2) numerically and minimizing the absolute deviations between the theoretical model option price (A-OPM) from Eq. (2) and the observed market price (for ATM options on S&P500) as implied by CBOE's VIX over a one-month maturity (T = 1 m), we can elicit investors subjective implied uncertainty attitudes (aversion IUA vs. seeking IUS) as follows:

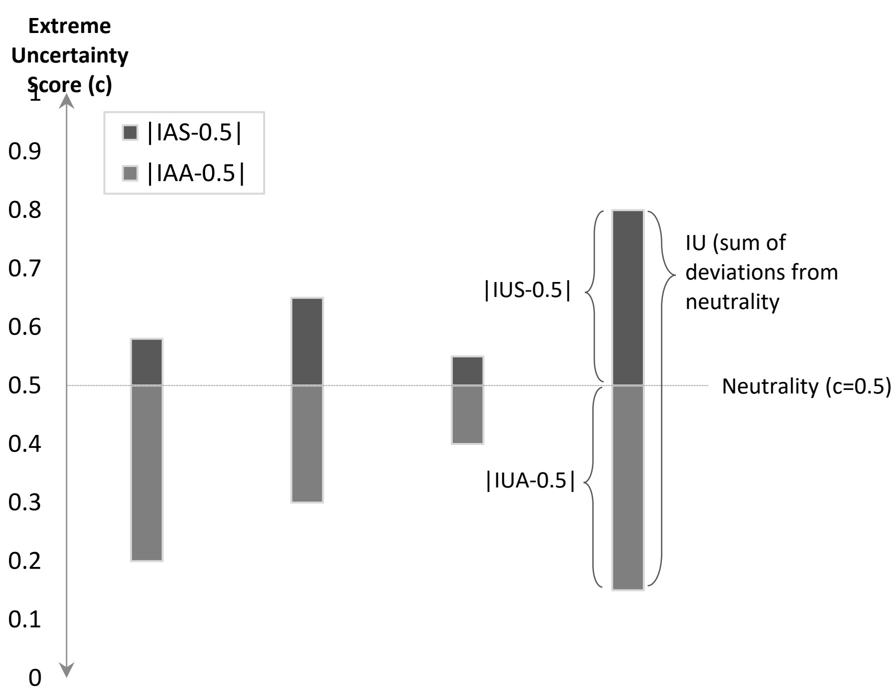
$$IUA_t \equiv c_t^{AA} = \underset{c|0<c\leq 0.5}{\arg\min}\left\{\left|C_t^A(S_t, K, r, T, \sigma_t, \mu_t, c_t) - C_t^{Mkt}(S_t, K, r, T, VIX_t)\right|\right\} \tag{6}$$

$$IUS_t \equiv c_t^{AS} = \underset{c|0.5\leq c<1}{\arg\min}\left\{\left|C_t^A(S_t, K, r, T, \sigma_t, \mu_t, c_t) - C_t^{Mkt}(S_t, K, r, T, VIX_t)\right|\right\} \tag{7}$$

C_t^A is the theoretical extreme uncertainty-based call option price according to our A-OPM of Eq. (2), C_t^{Mkt} is the market option price, S_t is the closing level of the S&P 500 index on day t, K, r, and T are as defined before, σ_t is market return volatility (estimated using RiskMetrics EWMA), c_t is the capacity measure, μ_t is the required rate of return (estimated as average return over the previous year), and VIX_t is the closing level of CBOE's VIX on day t. The above procedure allows to elicit option-based uncertainty information over a longer and continuous time window (1990-2012). Even though the A-OPM model assumes a constant c until the option matures, we are able to estimate c_t on a daily basis reflecting changing investors' attitudes to extreme uncertainty. This is similar to the computation of Black Scholes implied volatility on a daily basis (e.g., Rappoport & White 1994) where the B-S assumption of constant volatility does not undermine the ability to obtain a new estimate of volatility whenever the price changes. Our conclusions are unchanged if we use raw option prices rather than VIX for market uncertainty-elicitation.

The resulting capacity variable (c_t) inferred from numerically solving Eqs. (6) and (7) gives the degree of market investor implied uncertainty aversion (IUA, when c < 0.5) or implied uncertainty seeking (IUS, when c > 0.5) reflected in option prices or the VIX. Once market investors' heterogeneous beliefs or time-varying uncertainty aversion attitudes are obtained, we estimate aggregate implied market uncertainty on day t (IU_t) as the sum of deviations or distances of each of the implied uncertainty aversion or seeking beliefs (IUA and IUS) from neutrality (c = 0.5):

$$IU_t = (|IUS_t - 0.5| + |IUA_t - 0.5|) \tag{8}$$



The above is related to Abdellaoui et al. (2011) who estimate extreme uncertainty through deviations from Bayesian expected-utility and to Kast et al. (2014) who apply the Choquet framework to the Intertemporal CAPM (Merton, 1973). For robustness, we also use a variant of IU that is based on the sum of squared deviations from neutrality. Other related measures of heterogeneity in beliefs or uncertainty relying on deviations from a norm include dispersion in analysts' forecasts and survey-based disagreement among professional forecasters (Anderson et al. 2009). Our uncertainty proxy is elicited directly from market-observed option pricing dynamics. It is also indirectly related to the variance risk premium (VRP), the difference between "risk-neutral" expected stock market variance (VIX2) (corresponding to c = 0.5 in Eq. (2)) and (actual or "physical") realized variance (RV). In light of this shared commonality in information sources, we include VIX and VRP as part of a set of instruments used to orthogonalize market-elicited uncertainty in our long horizon predictive regressions.

In line with Bali & Zhou (2016) and Bekaert & Hoerova (2016), we compare the correlations between IU and established economic uncertainty proxies to validate the suitability of IU as a market-based proxy for aggregate uncertainty. Table 1 reports correlations between IU and both statistical- and survey/media-based macroeconomic uncertainty proxies. For statistical-based uncertainty measures, we consider the conditional variance of the Chicago Fed National Activity Index (CV_{CFNAI}) and of industrial production growth (CV_{IP}) estimated using GARCH(1,1) models (Bollerslev, 1986); the macroeconomic uncertainty measure ($MUNC_{BBC}$) of Bali, Brown, & Caglayan (2014) based on Principle Component Analysis (PCA); macroeconomic uncertainty ($MUNC_{JLN}^{1M}$ etc.) of Jurado, Ludvigson, & Ng (2015) measured by a weighted conditional variance of financial and macroeconomic series forecast errors with 1-, 3-, and 12-month forecasting horizons; and Scotti's (2016) surprise ($SURP_{Scotti}$) and uncertainty (UNC_{Scotti}) indices. For survey/media-based uncertainty measures, we consider the University of Michigan's Consumer Sentiment Index (UMCSI); the Consumer Confidence Index (CCI); the disagreement among economic forecasters from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters ($SPF_{CQ}\ etc.$) with different forecasting horizons; and the Economic Policy Uncertainty Index (PUI) of Baker, Bloom, & Davis (2016). The aforementioned measures have been used in contexts concerned with extreme uncertainty, and with economic and financial uncertainty or belief disagreement (e.g., Bloom, 2009; Bali et al., 2014; Bekaert et al., 2016).

Panel A of Table 1 confirms that the correlations between IU and each of the statistical-based macroeconomic uncertainty measures are all significant. The negative correlation between IU and $SURP_{Scotti}$ is reasonable since the surprise index is meant to capture forecasters' optimism. Out of the statistical-based macro uncertainty indicators, Jurado, Luvigson, & Ng's (2015) measures are known to have relatively less noise (Bekaert & Hoerova, 2016) due to their reliance on forecasting errors with many economic time series. The correlation between IU and $MUNC_{JLN}$ with different forecasting horizons ranges from 0.386 to 0.405, with the expected positive signs. In Panel B of Table 1, IU is seen to be significantly correlated with all survey/media-coverage based uncertainty proxies, except for the consumer confidence index (CCI). Among this group of uncertainty indicators, IU shows the highest correlation of 0.356 with SPF_{4Q}, which measures the dispersion in forecasts among professional forecasters for GDP growth four quarters ahead. The above correlations confirm the validity of IU as a proxy for uncertainty in the economy. With a relatively simple elicitation methodology from market options data, IU is thus seen to capture a rich set of macroeconomic uncertainty information on a real-time basis.

2.3 Empirical Methodology

To examine the behavior of a range of economic indicators representing various aspects of the real economy in response to economic shocks we employ a five-variable VAR system which, besides implied market uncertainty (IU), includes industrial production growth (IP), total non-farm payroll growth (TNP), personal consumption expenditure per capita growth (PCE), and changes in the Chicago Fed National Activity Index (CFNAI):

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{5,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_5 \end{bmatrix} + \begin{bmatrix} a_{1,1}^1 & a_{1,2}^1 & \cdots & a_{1,5}^1 \\ a_{2,1}^1 & a_{2,2}^1 & \cdots & a_{2,5}^1 \\ \vdots & \vdots & \ddots & \vdots \\ a_{5,1}^1 & a_{5,2}^1 & \cdots & a_{5,5}^1 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{5,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{1,1}^5 & a_{1,2}^5 & \cdots & a_{1,5}^5 \\ a_{2,1}^5 & a_{2,2}^5 & \cdots & a_{2,5}^5 \\ \vdots & \vdots & \ddots & \vdots \\ a_{5,1}^5 & a_{5,2}^5 & \cdots & a_{5,5}^5 \end{bmatrix} \begin{bmatrix} y_{1,t-5} \\ y_{2,t-5} \\ \vdots \\ y_{5,t-5} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{5,t} \end{bmatrix} \tag{9}$$

In Eq. (9) above, $y_{1,t}$ to $y_{5,t}$ represent each of the five variables at time t including IP, TNP, PCE, CFNAI, and IU.

This VAR system considers the dynamics between market-elicited implied uncertainty (IU) and changes in economic activity. We use variance decomposition, Granger causality and impulse-response for this purpose. After the VAR analysis, we investigate the predictive ability of market-elicited uncertainty over intermediate horizons (up to eight quarters).

In ascertaining the relationship between market uncertainty and ex post economic activity, we consider an extensive set of real economic activity indicators, two per sector. These indicators include: growth in industrial production (IP) and capacity utilization (CU) as measures of production activity; growth in total non-farm payroll (TNP) and in unemployment rate (UR) as measures of (un)employment; growth in personal consumption expenditure (PCE) and durable goods consumption (DG) as measures of consumption activity; and growth in real GDP per capita (GDPC) and the Chicago Fed National Activity Index (CFNAI) as measures of overall economic performance. The above eight indicators are used to test the impact of market-elicited uncertainty on real economic activity. Since production drives demand for labor (employment), which in turn affects consumption decisions, we investigate the relationship between market uncertainty and real economic activity in the following order: production, employment, and consumption. After analysing the effect of market-elicited uncertainty on each of these categories of economic activity, we focus on the bigger picture examining general economic output (based on real GDP growth per capita and the CFNAI indicators).

In the prediction part we employ standard long-horizon predictive regressions (e.g., Fama, 1990; Schwert, 1990; Cochrane, 1991; Carroll, Fuhrer, & Wilcox, 1994; Yang, 2011; Chen & Zhang, 2011) with various lags predicting subsequent economic activity using a time-varying orthogonalized or residuals-based variant of market uncertainty IUR. This helps control for possible extreme uncertainty effects from other predictor variables. Since IU captures deviations from risk-neutrality in Eq. (8), the use of a residuals-based IU measure, IUR, helps avoid multicollinearity problems and control for confounding effects from other established market-based predictors. The orthogonalized IU measure is specified by a Tobit regression as follows (see independent variables descriptions in Section 3):

$$IU_t = \alpha + \beta_1 VIX_t + \beta_2 VRP_t + \beta_3 DY_t + \beta_4 EP_t + \beta_5 ER_t + \beta_6 CS_t + \beta_7 TS_t + \varepsilon_t \qquad (10)$$
$$IU_t^R = \varepsilon_t$$

Our standard predictive regressions take the form:

$$y_{t+k}^{i} = \alpha + \beta x_{t}^{j} + \varepsilon_{t+k} \tag{11}$$

where y_{t+k}^{i} is ex post economic activity growth over k-months for economic indicator i, x_{t}^{j} is a 1 x h row vector of explanatory variables (excluding the intercept), α is an h x 1 vector of intercepts, and β is an h x 1 vector of slope coefficients. To address the overlapping data issue arising from the measurement of long-horizon growth (where k > 1) and for comparability purposes, we follow the extant literature employing robust t-statistics based on Newey and West (1987) standard errors (e.g. De Lint & Stolin, 2003; Chen & Zhang, 2011; Yang, 2011; Allen, Bali, & Tang, 2012; Bekaert & Hoerova, 2014).

2.4 Real Economic Activity Data and Variables Description

Dependent Variables

Production. In examining the predictive ability of market uncertainty concerning the growth of future production, we employ two indicators: growth in industrial production (IP) and growth in capacity utilization (CU). Monthly data on industrial production and capacity utilization from December 1989 to December 2014 are obtained from the Board of Governors of the Federal Reserve System. IP and CU are computed as the logarithmic change of the relevant indicator over a k-month horizon. Since industrial production values are denoted in real terms, no inflation adjustment is needed.

Employment. We use the unemployment rate growth (UR) and total non-farm payroll growth (TNP, net hiring) as indicators of employment activity. Monthly data of total non-farm payroll and unemployment rate from December 1989 to 2014 are obtained from the Bureau of Labor Statistics. UR and TNP are computed as logarithmic change of the indicator over a horizon of k months.

Consumption. For consumption indicators, we consider personal consumption expenditures growth (PCE) and personal consumption expenditures on durable goods consumption growth (DG). Monthly consumption data covering December 1989 to December 2014 are obtained from the Bureau of Economic Analysis (BEA). All values are divided by population and adjusted by the consumer price index (CPI) to obtain real consumption per capita. PCE and DG are the logarithmic change of the relevant per capita indicator in real terms over k month(s).

Overall Economic Output. We also investigate the relationship between IU and overall economic activity. We consider real gross domestic product (GDP) per capita and the Chicago Fed National Activity Index (CFNAI) as overall economic indicators. Quarterly data of real GDP is collected from the BEA. Real GDP per capita growth (GDPC) is computed as the logarithmic change of the relevant indicator over q quarter(s). Changes in aggregate economic output proxied by the CFNAI are computed as the average of the index over a k-month horizon.

Main Predictor Variables and Controls

We estimate market-elicited implied uncertainty (IU) based on Equations (2)-(8) using the closing level of the VIX index obtained from the Chicago Board Options Exchange (CBOE). Our option dataset covers the period from January 1990 to December 2012 when VIX data are available. We limit our dataset to a period up to 2012 to allow a 24-month window for the prediction of growth rates for the various economic indicators. To obtain IU, besides the VIX index closing levels, we estimate other inputs needed for our calibration and option pricing model. We use the one-month USD LIBOR as the risk-free interest rate (r), the one-year geometric return on the S&P 500 index as a proxy for the required return for S&P 500 investors (μ), and RiskMetrics EWMA volatility as the S&P return volatility measure (σ). Results are robust to alternative input estimations.

Since IU comes from the financial market and to avoid multicollinearity or confounding effects from other known market-based predictor variables, we use IUR in our predictive regressions. In orthogonalizing market uncertainty, we control for the aggregate dividend yield (DY) on the S&P 500 index (Yang, 2011), the term spread (TS) calculated as the difference between 10-year T-bond and 1-year T-bill yields (Plosser & Rouwenhorst, 1994; De Lint & Stolin, 2003; Estrella, 2005; Ang, Piazzesi, & Wei, 2006; Chen & Zhang, 2011), the credit spread (CS) computed as the difference between Moody's BAA and AAA yield indices (Gilchrist, Yankov, & Zakrajšek, 2009; Chen & Zhang, 2011), option implied volatility of the S&P 500 index as measured by the CBOE VIX (Bloom, 2009; Bekaert & Hoerova, 2014), market excess return (ER) (Fama, 1981; Barro, 1990; Schwert, 1990; Beaudry & Portier, 2006) of the S&P 500 index as measured by the monthly logarithmic return of S&P 500 index in excess of the logarithmic yield of 3-month treasury bills, the aggregate price-to-earnings ratio (EP) (Rapach, Strauss, & Zhou, 2010) of S&P 500 index constituents, and the variance risk premium (VRP) (e.g., Zhou, 2009; Bekaert & Hoerova, 2014) as measured by the difference between S&P 500 index implied variance (VIX2) and the realized variance computed as the sum of squared returns using intra-day 5-mins index data. As our uncertainty indicator is a market-based predictor, we restrict comparison to market-based predictors for fair comparison.

Aggregate DY and EP data are from Robert Shiller's website. US 10-year T-bill, 1-year T-bill yields, Moody's BAA yield index and Moody's AAA yield index data for computing the term and credit spreads (TS and CS) are from the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data (FRED). S&P 500 index data for calculation of monthly excess returns are from Thomson Reuters Datastream. VRP data is obtained from Hao Zhou's website. A summary of all above variables is provided in Table 2.

2.5 Main Results

In this section, we report and discuss our empirical results concerning the relationship between market-elicited implied uncertainty (IU) and subsequent real economic activity. We first investigate the statistical causal link between market uncertainty and economic activity. We then examine the informational efficiency of market uncertainty in predicting economic activity covering production, employment, consumption and overall output.

2.5.1 Summary Statistics

Exhibit 1 plots the time-varying levels of market implied uncertainty (IU) compared to option implied volatility (CBOE's VIX) and each of the eight economic activity indicators, with shaded areas representing NBER recessions. Graph 1 reveals prolongedly inflated IU values during the more uncertain periods (recessions), including the 1990 recession, the 1999 dot-com bubble, the 2008 financial crisis, and the 2010 Eurozone debt crisis. Market-elicited implied uncertainty IU is seen to be positively but loosely correlated with the VIX as shown in Graph 2 and exhibits volatile fluctuations. The IU plot in Graph 1 also has some resemblance to (and sometimes leads) the other graphs (shown in pairs) in Figure 1 depicting fluctuations in production (Panel B), employment (Panel C), consumption (Panel D), and overall economic output (Panel E).

Table 3 Panel A reports the descriptive statistics of the eight indicators of economic activity and the eight standard market predictor variables concerning risk, uncertainty, equity and bond fundamentals (summarized in Table 2). All statistics for the market predictor variables and indicators of economic activity are based on monthly observations, except for GDPC that is based on quarterly observations. Among the predictor variables, IU, ER and VRP show low levels of first-order autocorrelation (ranging from 0.07 to 0.36). Other predictor variables including DY, EP, CS, TS and VIX generally show very high first-order autocorrelations (ranging from 0.85 to 0.99 based on monthly observations). In light of the high persistence of these predictor variables, adjusted R2 needs to be interpreted with care. The low first-order autocorrelation of our uncertainty measure largely mitigates the concern of spurious regressions when compared to highly auto-correlated predictor variables such as VIX, CS, EP, TS and DY. Although recognizing inference concerns regarding these highly persistent standard predictor variables, they are considered for benchmarking and comparability with extant research. Concerning the basic descriptive statistics of the economic activity indicators, their comparative annualized mean growth rates provide a good snapshot of the aggregate state of the US economy during the last two decades. Real industrial production (mean IP of 2%) grew slower than overall per capita economic growth (mean GDPC of 4.15%), while real consumption per capita (mean PCE of 4.83%) grew in pace with overall per capita real economic growth.

Panel B of Table 3 reports the correlation matrix of the predictor variables and economic indicators based on monthly data. Correlations among contemporaneous predictor variables are generally low except for those between CS and VIX ($\rho = 0.61$) and EP and VIX ($\rho = -0.44$). In the analysis of predictive power of market uncertainty, we rely on the residuals-based IU (IUR). By comparison, the correlation matrix based on quarterly data in Panel C of Table 3 confirms that correlations among predictor variables are generally in line with those of the monthly sample (Panel B), except for VRP. When sampled with a quarterly frequency, the correlation between VRP and VIX, one of the sources of VRP's information extraction, increases from 0.31 to 0.72. This is likely due to the mean-reverting property of the realized volatility component of VRP. By contrast, though also relying on VIX as a main information source, IU's correlation with VIX declines from 0.37 to 0.28 in quarterly data, suggesting that IU and VIX contain different sets of information for different sampling frequencies.

2.5.2 Impact of Market Uncertainty on Real Economic Activity

In investigating the impact of market uncertainty on various sectors of the real economy, we employ a five-variable VAR system using industrial production growth (IP), total non-farm payroll growth (TNP), personal consumption expenditure per capita growth (PCE), and changes in the

Chicago Fed National Activity Index (CFNAI), in addition to market-elicited implied uncertainty (IU). We specify the VAR system according to Eq. (9) with a constant and five lags based on minimization of the Akaike information criterion.

Table 4 summarizes our variance decomposition and Granger causality results. Panel A gives the percentage of 24-month forecast error variance explained by innovations (shocks) in each variable based on the VAR system, while Panel B reports the p-value from Granger causality analysis. Panel A of Table 4 indicates that market-elicited uncertainty IU is only minimally explained by the other four economy indicators considered in the system. Among the four economic indicators, TNP does best but only explains 3.86% of the 24-month forecast error in IU. By contrast, IU seems to explain better the forecast error variance of all four economic indicators. IU explains 22.88% of CFNAI's and 25.22% of TNP's forecast error variance, 12.68% of IP's and 6.22% of PCE's. These results suggest that market implied uncertainty is important in explaining the forecast variance in the main economic indicators.

To help further understand the impact of market uncertainty on real economic activity, Granger causality results are presented in Panel B of Table 4. IU explains in a Granger-causal sense all four economic indicators at the 95% confidence level (p-value < 0.05). In terms of causal relationships in the reverse direction, none of the four economic activity indicators Granger-causes IU in the system. We further perform impulse response analysis (shown in Exhibit 2) to guide as to the signs expected for long-horizon predictions (up to 24 months). Exhibit 2 suggests that industrial production IP, employment measured by TNP, and overall output measured by CFNAI respond negatively to shocks in market-elicited implied uncertainty (IU) throughout a majority of the 24-month lags considered. PCE generally also responds negatively to shocks in IU in the first two month lags. The above impulse-response analysis broadly confirms the findings obtained from the previous variance decomposition and Granger causality tests, suggesting that market-elicited unecrtainty is a significant determinant of real economic activity. Given the confirmed negative impact of market uncertainty on economic activity, we next turn to examining the informational efficiency of market-elicited uncertainty in long-horizon predictions of real economic activity.

2.5.3 Predictive Ability of Market Implied Uncertainty

Having established the causal relationship between market implied uncertainty and real economic activity, we turn to investigate the usefulness of IU for economic policy forecasts. To ensure that the predictive performance of IU is not due to potential information overlaps with the other financial market predictors of economic activity, we employ residual IUR in our analysis. By orthogonalizing IU, the potential problem of multicollinearity between predictors can be ruled out (e.g., Aharony, 1986; Johnson 2004; Longstaff et al., 2011). To calculate IUR, we first regress IU on the seven contemporaneous predictor variables VIX, VRP, DY, EP, ER, CS and TS using a Tobit regression as in Eq. (10). The resulting residuals from the regression is used as the orthogonalized market implied uncertainty score (IUR) employed to predict production, employment, consumption and overall economic output activity in line with Eq. (11).

The predictive performance of the (othogonalized) market implied uncertainty indicator IUR is reported in Table 5. Panel A of Table 5 shows the strong predictive power of IUR for production activity. Market-elicited uncertainty predicts both industrial production growth (IP) and changes in capacity utilization (CU) from 1 up to 7 or 8 quarters. The consistently negative and significant coefficient of IUR confirms real option theory predictions on how increased economic uncertainty suppresses production, validating our Granger-causality results.

Turning to employment, Panel B of Table 5 reports the predictive regression results for changes in total non-farm payroll (TNP) and changes in unemployment rate (UR). IUR consistently predicts both indicators of employment activity for all horizons from 1 to 8 quarters. The predictive power for employment activity is highest at the 8-quarter horizon for both indicators and is highly significant. The negative (positive) coefficients in predicting TNP (UR) validate predictions from real options, as well as precautionary savings and financial frictions theories. Results from Panel B confirm that IU harbors a unique set of additional information and is an efficient predictor of employment activity.

The predictive regression results of consumption activity are reported in Panel C of Table 5. In line with findings from Panels A and B, IUR predicts both consumption indicators for all horizons considered. Market-elicited uncertainty predicts PCE and DG with robust t-statistics ranging from -1.7 to -2.3 and -1.82 to -2.1, respectively. The consistently negative predictive coefficients in Panel C validate the hypothesis of a negative relationship between extreme uncertainty and subsequent consumption.

Panel D of Table 5 reports the predictive regression results for real GDP per capita growth (GDPC) and the Chicago Fed National Activity Index (CFNAI). The orthogonalized market uncertainty score consistently predicts both indicators of overall output for all horizons considered. Once again our findings document a negative relationship between uncertainty and overall output.

2.6 Discussion and Implications

From the above analysis we conclude that our market implied uncertainty measures, IU and IUR, contain unique incremental information on future aggregate economic activity. We highlight a robust negative relation between extreme uncertainty elicited from the financial markets and a broad set of real economic activity indicators. For robustness, we additionally extract market-elicited uncertainty from traded option prices and find that the predictive power of IU holds. Our results also hold when relative risk aversion (RRA), estimated using a consumption-based asset pricing model, and time-varying risk aversion, as proxied by the Sharpe ratio, are controlled for.

We have thus identified a linkage between market implied uncertainty and macroeconomic activity based on U.S. data over the period 1990 to 2014. Using a 5-variable VAR system, market uncertainty is seen to (Granger) cause changes in production, employment, consumption and overall economic output. Variance decomposition analysis reveals significant portions of these economic indicators can be explained by uncertainty shocks inferred from the financial markets. Our evidence documents a negative causal or lead-lag link between market uncertainty and subsequent real economic activity. The degree of economic prediction is extended over at least eight quarters. Our market-based uncertainty measure consistently predicts all major U.S. economic performance indicators over the last quarter century, confirming a negative relationship between market uncertainty and various aspects of economic activity, in line with option theory.

The ability to predict economic performance is key to policy making and monitoring the real economy in uncertain and unpredictable times. The efficiency of our market-elicited uncertainty measure in predicting a wide range of economic indicators over the intermediate term might be useful in improving economic forecasts, in gauging the state of the economy and in implementing robust macroeconomic policies.

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FIGURE 1. Summary of Main Assumptions and Input Parameters

Cooperation/Fight multiple (*m*)

Cooperation (*c*)	1.20
Fight (*f*)	0.70

Market power share (s)

	FIRMS			
	Symmetric		Asymmetric	
INNOVATION ADVANTAGE	A	B	A	B
No	50%	50%	25%	75%
Small/Incremental	60%	40%	40%	60%
Large/Radical	75%	25%	50%	50%

Patent Wall multiplier (*W*)

	FIRM	
	A	B
Cost Multiplier (*W I*)		
W_A	1.2	
W_B		1.3
Value Multiplier (*W' V*)		
W'_A	1.2	
W'_B		2.2

Bracketing Cost multiplier (*b*)

	FIRM	
	A	B
Cost Multiplier (*b*)	1.3	1.3

Licensing Fee (*F*)

	INNOVATION ADVANTAGE		
	No	Small	Large
HIGH DEMAND (H)	50%		
MEDIUM/LOW DEMAND (M/L)	40%		
MEDIUM DEMAND (M)		20%	
LOW DEMAND (L)			15%

Other valuation inputs

Investment cost (*I*): $ 80 million

Base volatility (σ): 60%

Cost of capital (k): 20%

Riskless interest rate (r): 8%

FIGURE 2. Innovation (Patent) Strategies Contingent on Innovation Advantage and State of Demand/Industry Dynamism

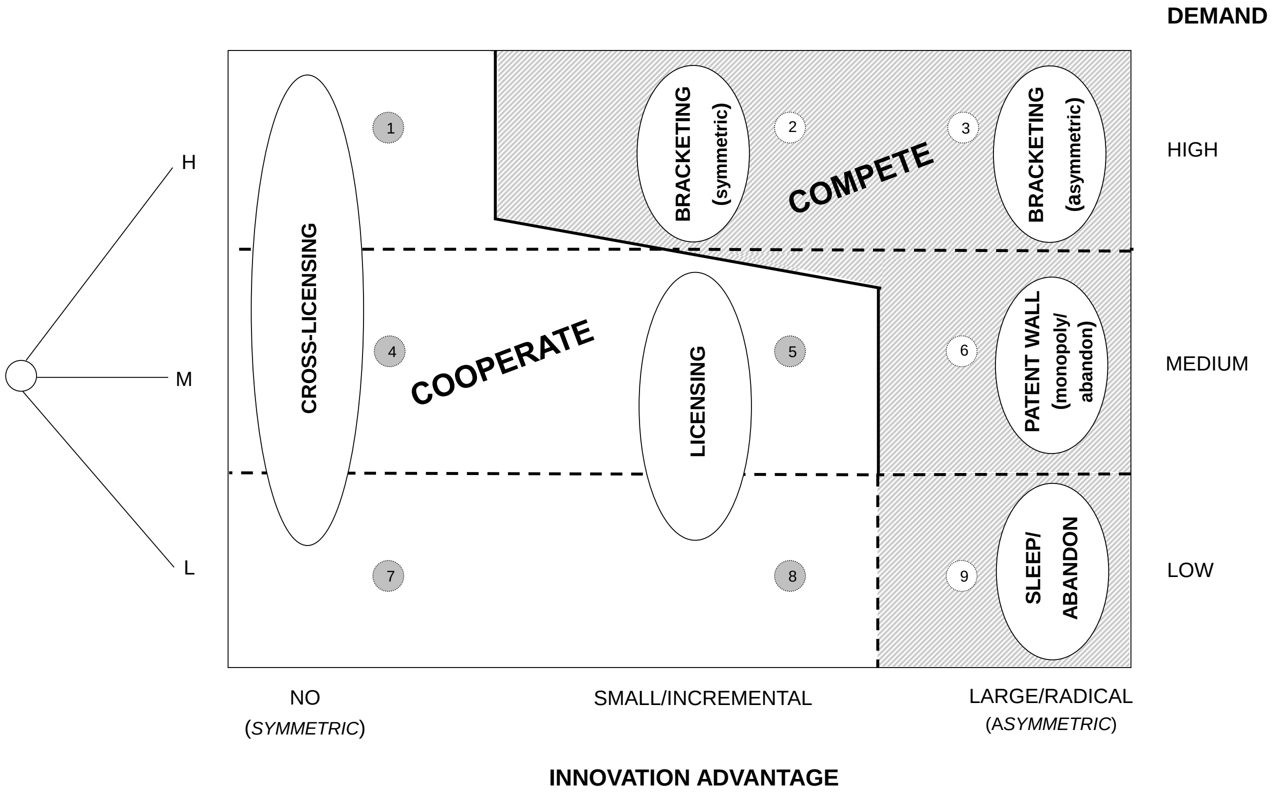


FIGURE 3. Value of Patent Strategy (S-NPV) for Varying Degrees of Innovation Advantage

Reflected in Market Concentration Index (HHI) and Different Volatility

under Compete, Cooperate and Hybrid Strategy (Asymmetric Duopoly)

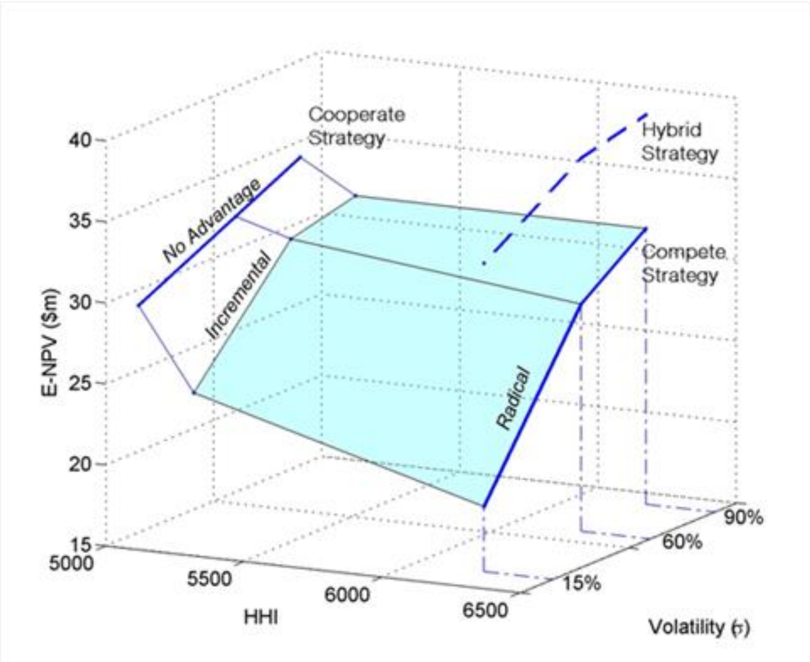


FIGURE 4. The Compete vs. Cooperate Tradeoff:

Sensitivity of S-NPV to *Cooperation* Multiple

(Under Large Advantage/Cooperation Stance)

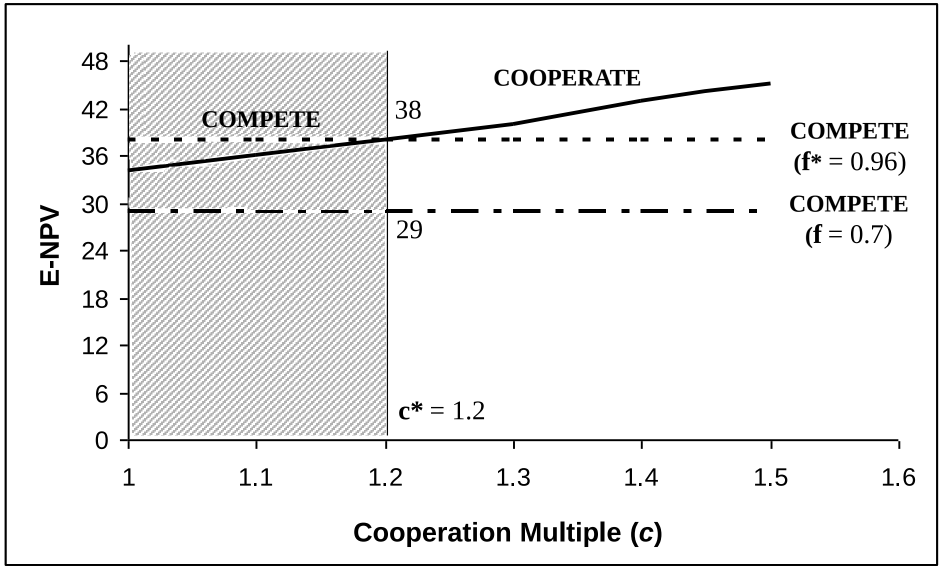


FIGURE 5A. Sensitivity of S-NPV to *Cooperation Multiple* for

Different Degrees of Innovation Advantage

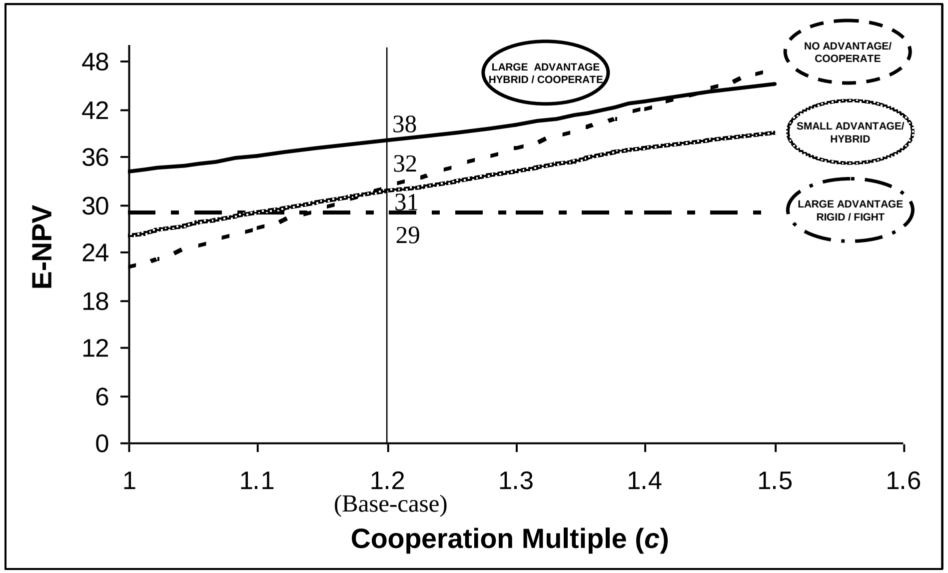


FIGURE 5B. Sensitivity of S-NPV to *Volatility* under No, Small or Large Innovation

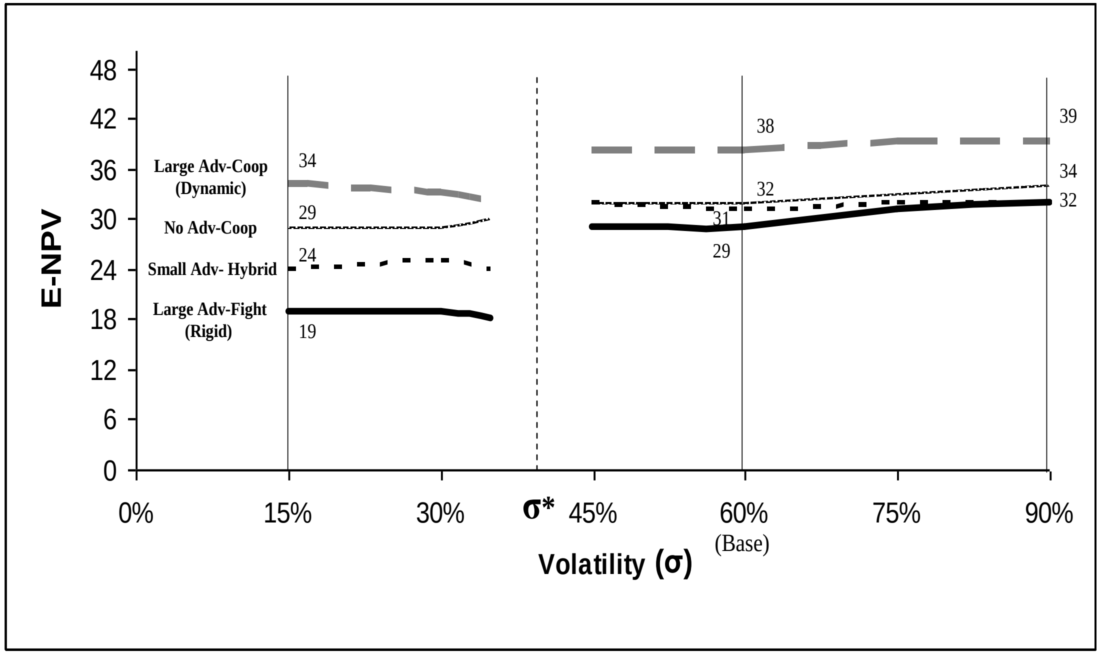
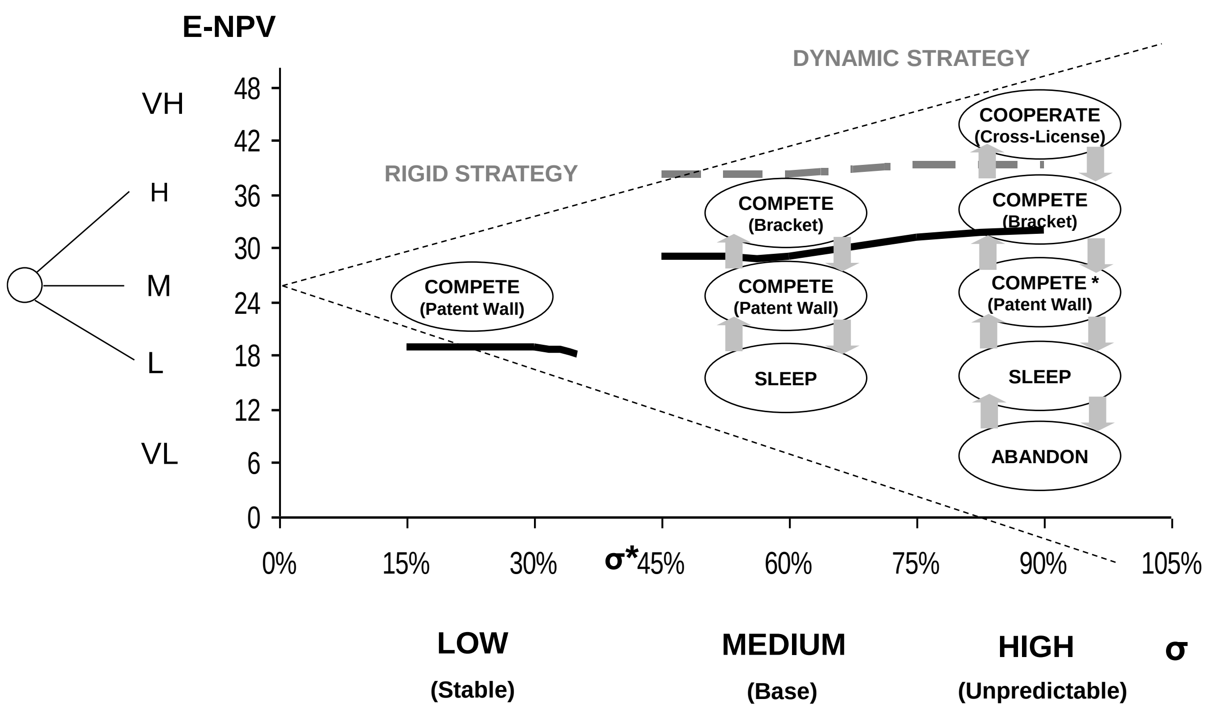


FIGURE 6A. Summary and Extension of Patent Strategies for a Broader Range of Demand Uncertainty (Under Large Innovation Advantage) – Symmetry Case



* Sometimes cooperate (e.g., cross-licensing against third rivals)

FIGURE 6B. Summary and Extension of *Compete vs. Cooperate* Strategies (for a Broader Range of Demand/Uncertainty) under No, Small or Large Innovation Advantage – Symmetry Case

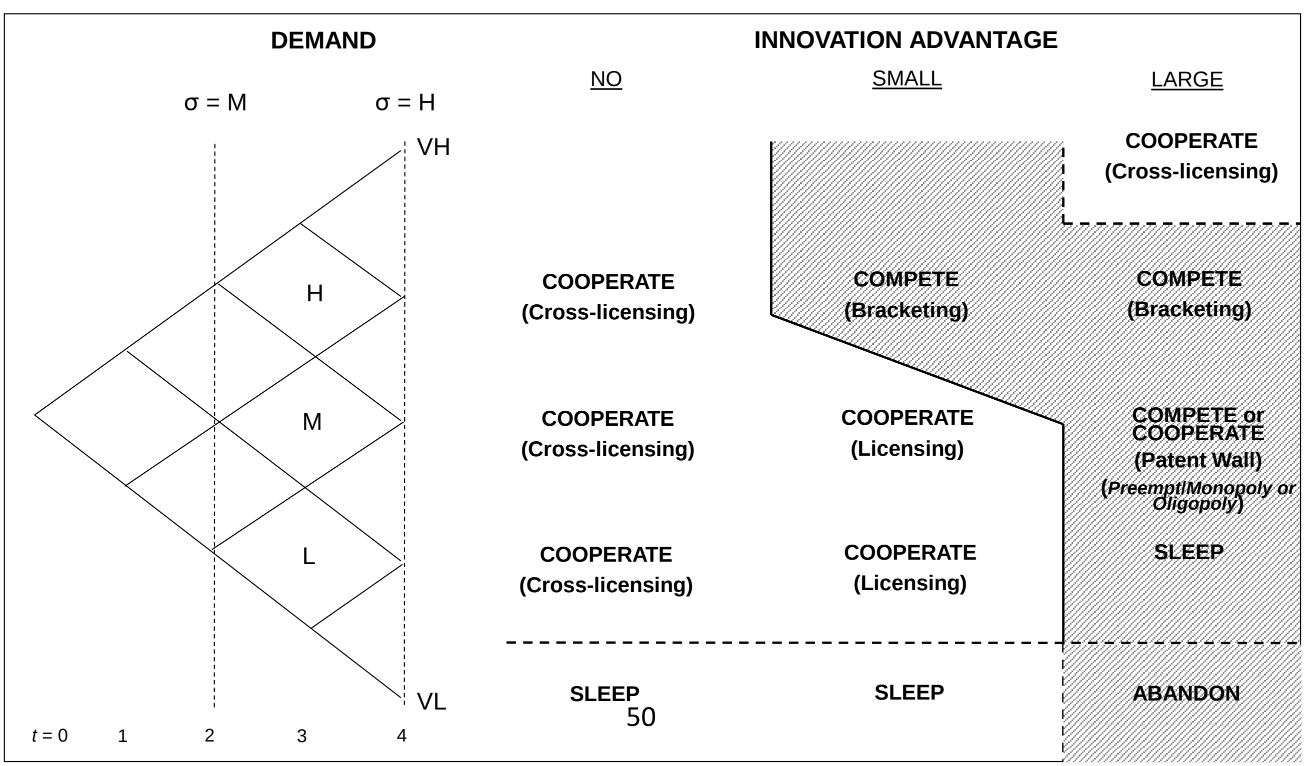
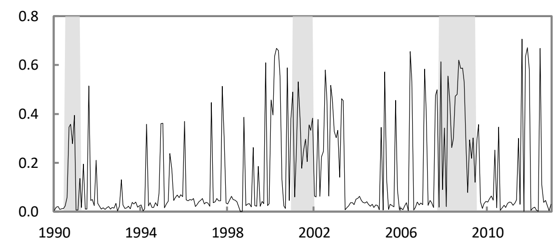


EXHIBIT 1

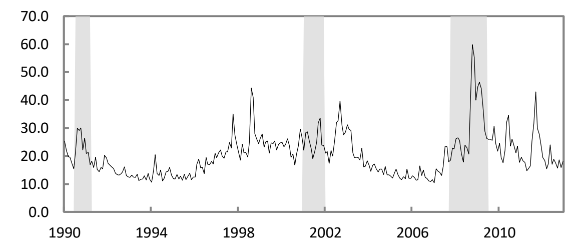
MARKET-ELICITED UNCERTAINTY, S&P 500 IMPLIED VOLATILITY AND ECONOMIC ACTIVITY INDICATORS

Panel A. Market Ambiguity

Graph 1 – Market-elicited Implied Unceratinty (IU)

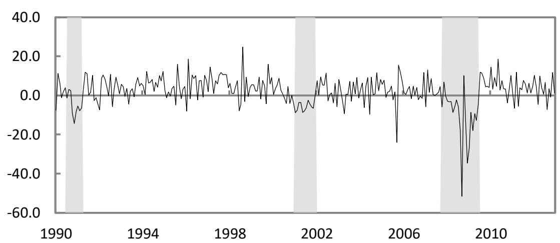


Graph 2 – Option Implied Volatility (VIX)

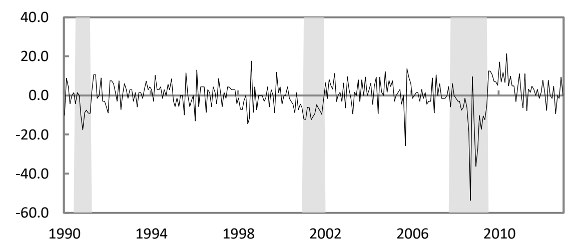


Panel B. Production

Graph 3 - Industrial Production (IP) Growth

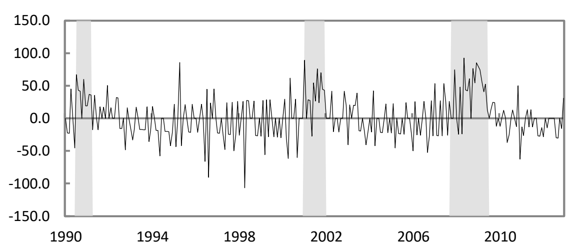


Graph 4 – Capacity Utilization (CU) Growth

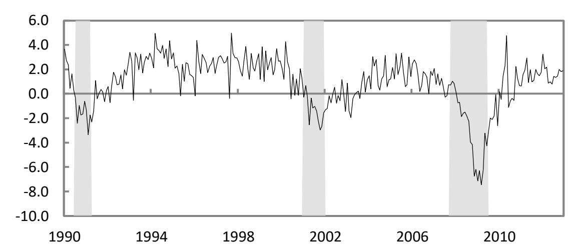


Panel C. Employment

Graph 5 – Unemployment Rate (UR) Growth

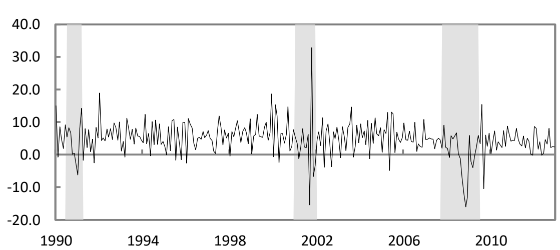


Graph 6 – Total Non-farm Payroll (TNP) Growth

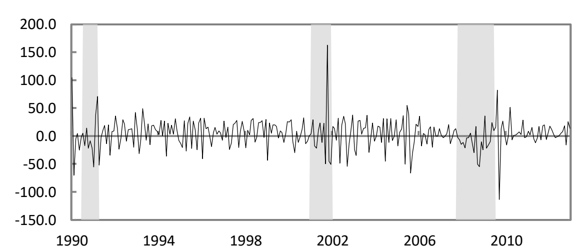


Panel D. Consumption

Graph 7 – Personal Consumption Expenditure (PCE) Growth

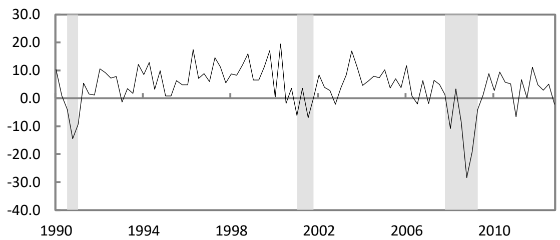


Graph 8 – Durable Goods Consumption (DG) Growth



Panel E. Overall Economic Output

Graph 9 – GDP Per Capita (GDPC) Growth



Graph 10 - Chicago Fed National Activity Index (CFNAI)

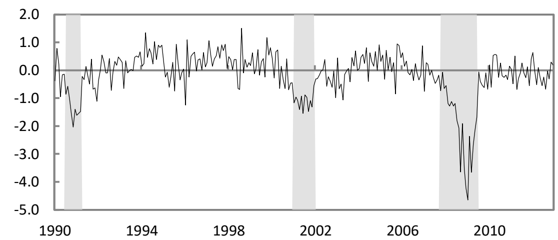
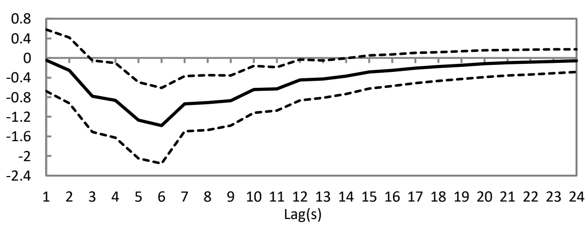


Figure 1 shows time-varying levels of market-elicited ambiguity, S&P 500 implied volatility and (pairs of) economic activity indicators concerning production, employment, consumption, and overall economic output. All variables are sampled with monthly frequency except GDPC which is sampled with quarterly frequency. Shaded areas represent NBER recession periods based on quarterly dates. The sample period spans Jan 1990 to Dec 2014.

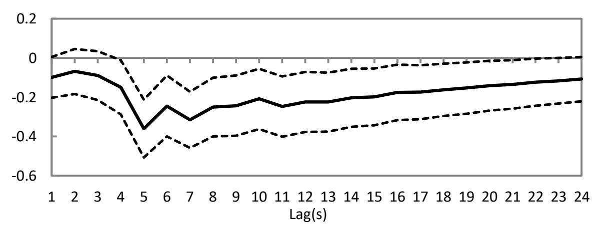
EXHIBIT 2

RESPONSES OF SELECT ECONOMIC INDICATORS TO SHOCKS IN MARKET-ELICITED UNCERTAINTY (IU)

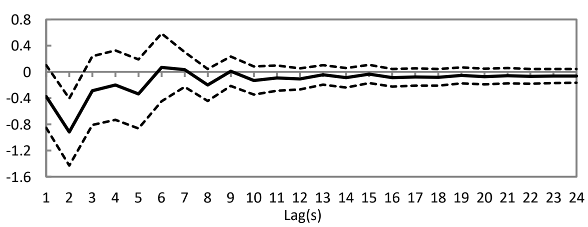
Panel A. Response of Industrial Production (IP) Growth to shock in IU



Panel B. Response of Total Non-farm Payroll (TNP) Growth to shock in IU



Panel C. Response of Personal Consumption Expenditure (PCE) Growth to shock in IU



Panel D. Response of Chicago Fed National Activity Index (CFNAI) to shock in IU

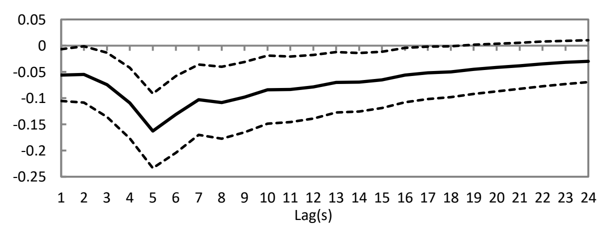


Figure 2 shows impulse responses of industrial production (IP) growth, total non-farm payroll (TNP) growth, personal consumption expenditure (PCE) growth, and the Chicago Fed National Activity Index (CFNAI) to shocks in IA. Dotted lines represent confidence bands at 90% level. The sample period spans Jan 1990 to Dec 2014.

TABLE 1

CORRELATIONS WITH MACROECONOMIC UNCERTAINTY PROXIES

Panel A. Correlations with statistical based measures

	IU		IU
CV_{CFNAI}	0.189***	$MUNC_{JLN}^{3M}$	0.393***
	(0.002)		(0.000)
CV_{IP}	0.190***	$MUNC_{JLN}^{12M}$	0.405***
	(0.002)		(0.000)
$MUNC_{BBC}$	0.159**	$SURP_{Scotti}$	-0.150***
	(0.017)		(0.014)
$MUNC_{JLN}^{1M}$	0.386***	UNC_{Scotti}	0.181***
	(0.000)		(0.003)

Panel B. Correlations with survey / media-coverage based measures

	IU		IU
CCI	-0.026	SPF_{2Q}	0.263**
	(0.667)		(0.011)
PUI	0.181***	SPF_{3Q}	0.283***
	(0.003)		(0.006)
SPF_{CQ}	0.240**	SPF_{4Q}	0.356***
	(0.021)		(0.001)
SPF_{1Q}	0.268***	$UMCSI$	-0.155***
	(0.010)		(0.010)

Table 1 reports correlations between market-elicited implied uncertainty IU and other established macroeconomic uncertainty proxies. CV_{CFNAI} is the conditional variance of the Chicago Fed National Activity Index estimated by GARCH(1,1); CV_{IP} is the conditional variance of industrial production growth estimated by GARCH(1,1); $MUNC_{BBC}$ is the macroeconomic uncertainty measure according to Bali, Brown, and Caglayan (2014); $MUNC_{JLN}^{1M}$, $MUNC_{JLN}^{6M}$, and $MUNC_{JLN}^{12M}$ are the macroeconomic uncertainty measures according to Jurado, Ludvigson, and Ng (2015) with 1-, 3-, and 12-month forecasting horizons, respectively;
$SURP_{Scotti}$ and UNC_{Scotti} are the surprise and uncertainty indices according to Scotti (2016). CCI is the consumer confidence index; PUI is the economic policy uncertainty index; SPF_{CQ}, SPF_{CQ}, SPF_{CQ}, SPF_{CQ}, and SPF_{CQ} are dispersion of the Survey of Professional Forecasters in forecasting GDP for current quarter, and 1-4 quarters ex post, respectively; $UMCSI$ is the University of Michigan Consumer Sentiment Index. Correlations are computed using monthly samples covering observations from 1990M01 to 2014M12. p-values are shown in parenthesis. *, **, and *** represent significance at 90%, 95%, and 99% confidence levels respectively.

TABLE 2

DESCRIPTIONS OF VARIABLES, DATA SERIES, AND DATA SOURCES

Panel A. Predictor Variables

Category	Abbreviation	Corresponding Indicator	Description	Source
Uncertainty Measures	IA	Market-elicited Ambiguity	Estimated by rank dependent option pricing model according to (8). End of month values.	-
	RV	S&P500 Realized Variance	Computed as the sum of squared returns using intra-day 5-min S&P500 index prices	Hao Zhou's website
	VIX	S&P500 Implied Volatility	S&P 500 option implied volatility based on the CBOE VIX index.	Chicago Board Options Exchange
	VRP	Variance Risk Premium	Variance risk premium defined as the difference between realized variance and implied variance of S&P 500 return.	Hao Zhou's website
Equity fundamentals	DY	Dividend Yield	Aggregate dividend yield of S&P 500 composite.	Robert Shiller's website
	EP	Earnings to Price Ratio	Reciprocal of aggregate price to earnings ratio of S&P 500 composite.	Robert Shiller's website
	ER	S&P500 Excess Return	S&P 500 index return in excess of 3-month treasury bond yield.	Thomson Datastream
Bond fundamentals	CS	Credit Spread (BAA yield - AAA yield)	Difference between Moody's BAA and AAA corporate bond yield.	Federal Reserve Bank of St. Louis FRED
	TS	Yield Curve (Term Spread, 10Y T-yield - 3M T-yield)	Difference between 10-year and 3-month U.S. treasury bond yield.	Federal Reserve Bank of St. Louis FRED

Panel B. Real Economic Activity Measures

Category	Abbreviation	Corresponding Indicator	Description	Source
Production	IP	Industrial Production Growth	Logorithmic change of k-month horizon industrial production index, measured as the real seasonally adjusted output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities.	Board of Governors of the Federal Reserve System
	CU	Capacity Utilization Ratio Growth	Logorithmic change of k-month horizon capacity utilization measured as the percentage of resources used by corporations and factories to produce goods in manufacturing, mining, and electric and gas utilities for all facilities located in the United State.	Board of Governors of the Federal Reserve System
Employment	TNP	Total Non-farm Payroll Growth	Logorithmic change of k-month horizon total nonfarm payroll, measured as the seasonally adjusted number of U.S. workers in the economy that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed.	U.S. Bureau of Labor Statistics
	UR	Unemployment Rate Growth	Logorithmic change of k-month horizon unemployment rate, measured as the seasonally adjusted number of unemployed as a percentage of the labor force.	U.S. Bureau of Labor Statistics
Consumption	PCE	Personal Consumption Expenditure Growth (Real, per capita)	Logorithmic change of k-month horizon personal consumption expenditure per capita, measured as the seasonally adjusted per capita real value of goods and services purchased by U.S. residents.	U.S. Bureau of Economic Analysis
	DG	Durable Goods Expenditure Growth (Real, per capita)	Logorithmic change of k-month horizon durable goods expenditure per capita, measured as the seasonally adjusted per capita real value of durable goods purchased by U.S. residents. Durable goods is defined as tangible commodities that can be stored or inventoried and that have an average life of at least 3 years.	U.S. Bureau of Economic Analysis
Overall Output	GDPC	Real GDP per Capita Growth	Logorithmic change of q-month quarter real gross domestic product per capita. Sample: 1990Q1 to 2014Q4.	U.S. Bureau of Economic Analysis
	CFNAI	Chicago Fed National Activity Index	Sum of k-month Chicago Fed National Activity Index.	Federal Reserve Bank of Chicago

Panel C. Macroeconomic Uncertainty Proxies

Category	Abbreviation	Corresponding Indicator	Description	Source
Statistical based measures	CV_{CFNAI}	Conditional Variance of Chicago Fed National Activity Index	Conditional Variance of Chicago Fed National Activity Index estimated by GARCH(1,1)	-
	CV_{IP}	Conditional Variance of Industrial Production Growth	Conditional Variance of Industrial Production Growth estimated by GARCH(1,1)	-
	$MUNC_{BBC}$	Bali et al (2014) Macroeconomic Uncertainty	Macroeconomic Uncertainty measure according to Bali, Brown, and Caglayan (2014)	Turan Bali's website
	$MUNC_{JLN}$	Jurado et al.(2015) Macroeconomic Uncertainty	Macroeconomic Uncertainty measure with 1-, 3-, and 12-month forecasting horizons according to Jurado, Ludvigson and Ng (2015)	Sydney Ludvigson's website
	$SURP_{Scotti}$	Scotti(2016) surprise index	Surprise index according to Scotti(2016)	Chiara Scotti's website
	UNC_{Scotti}	Scotti(2016) uncertainty index	Uncertainty index according to Scotti(2016)	Chiara Scotti's website
Survey / media-coverage based measures	CCI	Consumer Confidence Index	Consumer Confidence Index	Federal Reserve Bank of St. Louis FRED
	PUI	Economic Policy Uncertainty Index	Economic Policy Uncertainty Index	http://www.policyuncertainty.com/
	SPF	Forecast Dispersion for Survey of Professional Forecaster	Forecast Dispersion for Survey of Professional Forecaster in forecasting GDP for current quarter, and 1-4 quarters ex post	Federal Reserve Bank of Philadelphia website
	UMCSI	University of Michigan Consumer Sentiment Index	University of Michigan Consumer Sentiment Index	Federal Reserve Bank of St. Louis FRED

TABLE 3

DESCRIPTIVE STATISTICS AND CORRELATIONS

Panel A. Descriptive Statistics

	Predictor Variables								Real Economic Activity Measures							
	Uncertainty Measures			Equity Fundamentals			Bond Fundamentals		Production		Employment		Consumption		Overall Economic Activity	
	IA	*VIX*	*VRP*	*DY*	*EP*	*ER*	*CS*	*TS*	*IP*	*CU*	*TNP*	*UR*	*DG*	*PCE*	*GDPC*	*CFNAI*
Mean	0.15	20.43	18.47	2.10	4.67	6.03	0.97	1.88	2.02	-0.30	0.94	1.65	4.00	4.83	4.15	-0.17
Std. Dev.	0.20	7.77	20.35	0.66	1.40	52.51	0.42	1.16	7.98	8.00	2.10	31.67	26.52	5.16	7.59	0.86
Skewness	1.29	1.59	-2.48	0.66	-0.48	-0.77	3.06	-0.15	-1.74	-1.57	-1.22	0.29	0.36	-0.12	-1.28	-1.86
Kurtosis	0.29	4.04	35.17	-0.48	-0.10	1.57	12.23	-1.14	8.79	8.21	2.42	0.59	6.09	4.93	3.68	5.92
AR(1)	0.36	0.85	0.26	0.99	0.98	0.07	0.96	0.98	0.24	0.23	0.79	0.05	-0.26	-0.09	0.44	0.69

Panel B. Correlation Matrix for Monthly Sample

	IA	*VIX*	*VRP*	*DY*	*EP*	*ER*	*CS*	*TS*	*IP*	*CU*	*TNP*	*UR*	*DG*	*PCE*	*CFNAI*
IA	1.00														
VIX	0.37	1.00													
VRP	-0.20	0.31	1.00												
DY	-0.11	-0.04	-0.02	1.00											
EP	-0.16	-0.44	-0.20	0.26	1.00										
ER	-0.02	-0.39	-0.03	-0.02	0.06	1.00									
CS	0.30	0.61	0.04	0.29	-0.35	-0.13	1.00								
TS	-0.08	0.05	-0.03	0.35	-0.19	-0.04	0.27	1.00							
IP	-0.20	-0.25	-0.04	-0.13	0.20	0.02	-0.44	0.02	1.00						
CU	-0.18	-0.22	-0.06	-0.09	0.18	-0.01	-0.31	0.18	0.95	1.00					
TNP	-0.29	-0.51	-0.10	-0.24	0.43	0.13	-0.75	-0.24	0.53	0.40	1.00				
UR	0.17	0.28	0.05	0.15	-0.25	-0.09	0.37	0.04	-0.39	-0.35	-0.45	1.00			
DG	-0.10	-0.08	0.12	-0.07	-0.01	0.04	-0.13	0.00	0.10	0.07	0.15	0.00	1.00		
PCE	-0.19	-0.26	0.12	-0.15	0.05	0.11	-0.37	-0.08	0.24	0.20	0.32	-0.11	0.78	1.00	
CFNAI	-0.31	-0.49	-0.05	-0.28	0.31	0.12	-0.72	-0.08	0.82	0.74	0.82	-0.55	0.17	0.38	1.00

Panel C. Correlation Matrix for Quarterly Sample

	IA	*VIX*	*VRP*	*DY*	*EP*	*ER*	*CS*	*TS*	*GDPC*
IA	1.00								
VIX	0.28	1.00							
VRP	-0.14	0.72	1.00						
DY	-0.03	-0.04	0.03	1.00					
EP	-0.11	-0.42	-0.15	0.23	1.00				
ER	0.00	-0.24	-0.16	-0.05	0.00	1.00			
CS	0.39	0.56	0.15	0.28	-0.36	-0.05	1.00		
TS	-0.12	0.05	0.06	0.34	-0.20	-0.13	0.25	1.00	
GDPC	-0.38	-0.38	0.02	-0.37	0.15	0.14	-0.64	-0.06	1.00

Table 3 reports the descriptive statistics and correlation matrices. IU (or IA) is market-elicited implied uncertainty (or implied ambiguity). VIX is the CBOE volatility index. VRP is the variance risk premium calculated as the difference between implied variance and realized variance. DY is the dividend yield of the S&P 500 index. EP is the earnings to price ratio of the S&P 500 index. ER is the excess return of the S&P 500 index calculated as the logarithmic return of S&P 500 in excess of the logarithmic yield of 3M T-bill. CS is the credit spread between Moody's AAA and BAA bond yield indices. TS is the term spread between 10Y T-bond and 3M T-bill yields. IP and CU denote industrial production growth and capacity utilization ratio growth respectively. TNP and UR represent total non-farm payroll growth and unemployment rate growth respectively. PCE and DG denote personal consumption expenditure per capita growth and personal consumption expenditure on durable goods per capita growth respectively. GDPC denotes gross domestic product per capita growth. CFNAI is the Chicago Fed National Activity Index. All variables are reported in annualized percentage whenever possible. Descriptive statistics for predictor variables, production indicators, employment indicators, consumption indicators, and CFNAI are computed using monthly samples covering observations from 1990M01 to 2014M12. Descriptive statistics for GDPC are computed using quarterly data covering 1990Q1 to 2014Q4.

TABLE 4

VARIANCE DECOMPOSITION AND GRANGER CAUSALITY

Panel A. Variance Decomposition

Dependent	Explained by Innovations in				
Variable	*IA*	*IP*	*PCE*	*TNP*	*CFNAI*
	(%)	(%)	(%)	(%)	(%)
IA	88.42	3.01	1.77	3.86	2.94
IP	12.68	67.07	4.90	4.90	10.45
PCE	6.22	6.10	79.81	3.94	3.93
TNP	25.22	20.13	4.08	38.10	12.47
CFNAI	22.88	37.55	6.38	10.73	22.45

Panel B. Granger Causality

Dependent	Granger Caused by				
Variable	*IA*	*IP*	*PCE*	*TNP*	*CFNAI*
IA	-	0.69	0.12	0.93	0.75
IP	0.02	-	0.18	0.20	0.00
PCE	0.04	0.54	-	0.34	0.36
TNP	0.02	0.08	0.33	-	0.00
CFNAI	0.01	0.00	0.02	0.87	-

Table 4 reports the variance decomposition and Granger causality results. Panel A reports the 24-month forecast error variance explained by innovations (shocks) in each of the variables. Panel B reports the p-value of Granger causality tests with null hypothesis of no Granger causality. IU or IA is the market-elicited uncertainty or implied ambiguity. IP denotes industrial production growth. TNP represents total non-farm payroll growth. PCE denotes personal consumption expenditure per capita growth. CFNAI is the Chicago Fed National Activity Index. The VAR system includes monthly sample covering observations from 1990M01 to 2014M12.

TABLE 5

PREDICTIVE PERFORMANCE OF MARKET-ELICITED IMPLIED UNCERTAINTY

	Prediction Horizon (Quarters)							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Panel A: Predicting Production Activity								
Dependent Variable: Industrial Production Growth (IP)								
Cst	1.91	1.88	1.89	1.92	1.96	2.01	2.05	2.09
	(3.48)	(2.72)	(2.48)	(2.45)	(2.51)	(2.56)	(2.60)	(2.64)
IU^R	-6.12*	-7.32**	-6.71**	-6.94***	-6.73***	-6.08***	-5.44***	-4.36***
	(-1.90)	(-2.45)	(-2.40)	(-2.70)	(-3.00)	(-3.16)	(-3.38)	(-3.33)
Adj. R^2 (%)	2.81	5.36	5.31	6.71	7.41	6.98	6.38	4.53
Dependent Variable: Changes in Capacity Utilization Ratio (CU)								
Cst	-0.38	-0.41	-0.39	-0.36	-0.31	-0.26	-0.23	-0.19
	(-0.71)	(-0.60)	(-0.53)	(-0.49)	(-0.43)	(-0.37)	(-0.34)	(-0.28)
IU^R	-5.08*	-6.21**	-5.45**	-5.49**	-5.08**	-4.19**	-3.39**	-2.16
	(-1.67)	(-2.19)	(-2.04)	(-2.19)	(-2.29)	(-2.15)	(-2.04)	(-1.61)
Adj. R^2 (%)	1.86	3.89	3.60	4.46	4.66	3.79	2.94	1.24
Panel B: Predicting Employment Activity								
Dependent Variable: Changes in Total Non-farm Payroll (TNP)								
Cst	0.90	0.88	0.89	0.90	0.91	0.93	0.95	0.97
	(4.58)	(3.38)	(2.90)	(2.68)	(2.58)	(2.53)	(2.51)	(2.51)
IU^R	-1.63*	-2.29**	-2.41**	-2.55***	-2.61***	-2.56***	-2.49***	-2.34***
	(-1.78)	(-2.47)	(-2.54)	(-2.77)	(-3.02)	(-3.15)	(-3.40)	(-3.57)
Adj. R^2 (%)	1.58	3.78	4.51	5.43	6.14	6.35	6.46	6.10
Dependent Variable: Changes in Unemployment Rate (UR)								
Cst	1.99	2.00	1.85	1.65	1.43	1.19	0.97	0.75
	(1.02)	(0.83)	(0.67)	(0.56)	(0.47)	(0.38)	(0.30)	(0.23)
IU^R	16.97*	20.84**	22.39**	22.51***	23.15***	22.74***	20.85***	19.02***
	(1.72)	(2.22)	(2.40)	(2.65)	(2.99)	(3.18)	(3.23)	(3.32)
Adj. R^2 (%)	1.57	3.51	4.67	5.26	6.20	6.55	5.93	5.28
Panel C: Predicting Consumption Activity								
Dependent Variable: Changes in Personal Consumption Expenditure (PCE)								
Cst	4.75	4.74	4.73	4.73	4.73	4.74	4.74	4.75
	(17.40)	(15.01)	(13.55)	(12.83)	(12.32)	(11.94)	(11.64)	(11.37)
IU^R	-3.01*	-2.58*	-2.44*	-2.60**	-2.45**	-2.29**	-2.18**	-1.88**
	(-1.83)	(-1.74)	(-1.70)	(-2.09)	(-2.08)	(-2.17)	(-2.30)	(-2.08)
Adj. R^2 (%)	2.54	2.98	3.38	4.45	4.47	4.29	4.20	3.32
Dependent Variable: Durable Goods Consumption Growth (DG)								
Cst	3.60	3.74	3.82	3.89	3.94	4.01	4.07	4.11
	(3.97)	(4.44)	(4.30)	(4.19)	(4.18)	(4.16)	(4.15)	(4.15)
IU^R	-10.07*	-7.74*	-6.35*	-5.55*	-5.78**	-5.15**	-4.02*	-3.65*
	(-1.86)	(-1.85)	(-1.82)	(-1.86)	(-2.10)	(-2.02)	(-1.92)	(-1.86)
Adj. R^2 (%)	1.83	2.76	2.78	2.50	3.44	3.13	2.07	1.86
Panel D: Predicting Overall Output								
Dependent Variable: Real GDP Per Capita Growth (GDPC)								
Cst	1.39	1.40	1.42	1.45	1.47	1.48	1.50	1.51
	(5.42)	(4.97)	(4.71)	(4.70)	(4.62)	(4.52)	(4.45)	(4.33)
IU^R	-3.14*	-3.33**	-3.37**	-3.59***	-3.19**	-2.89**	-2.74**	-2.22**
	(-1.71)	(-2.44)	(-2.50)	(-2.83)	(-2.40)	(-2.28)	(-2.41)	(-2.06)
Adj. R^2 (%)	2.79	5.03	6.30	8.85	8.00	7.41	7.46	5.11
Dependent Variable: Chicago Fed National Activity Index (CFNAI)								
Cst	-0.19	-0.19	-0.19	-0.19	-0.18	-0.17	-0.17	-0.16
	(-2.46)	(-1.88)	(-1.64)	(-1.50)	(-1.39)	(-1.30)	(-1.24)	(-1.17)
IU^R	-0.75*	-0.92**	-0.95**	-0.98***	-0.97***	-0.91***	-0.84***	-0.73***
	(-1.80)	(-2.27)	(-2.38)	(-2.59)	(-2.81)	(-2.87)	(-3.02)	(-3.02)
Adj. R^2 (%)	2.24	3.97	4.79	5.63	6.19	6.00	5.61	4.57

Table 5 reports the predictive regression results for real economic activity including production, employment, consumption and overall output activity. IU^R is obtained as follows:

$$IU_t = \alpha + \beta_1 VIX_t + \beta_2 VRP_t + \beta_3 DY_t + \beta_4 EP_t + \beta_5 ER_t + \beta_6 CS_t + \beta_7 TS_t + \varepsilon_t$$

$$IA_t^R = \varepsilon_t$$

where IU is the market-elicited implied uncertainty (ambiguity). VIX is the implied volatility of the S&P 500 index based on the CBOE volatility index. VRP is variance risk premium, obtained as the difference between implied variance and realized variance of the S&P 500 index. DY is the dividend yield of the S&P 500 index. EP is the earnings to price ratio of the S&P 500 index. ER is the excess return of the S&P 500 index calculated as the logarithmic return of S&P 500 in excess of the logarithmic yield of 3M T-bill. CS is the credit spread between Moody's AAA and BAA bond yield indices. TS denotes the term spread between 10Y T-bond and 3M T-bill yields. The sample covers monthly observations from 1990M01 to 2014M12. Newey-West t-statistics with lags equal to the return horizon (in months) are reported in parentheses. *, **, and *** represent significance at 90%, 95%, and 99% confidence levels respectively.