Roles of commitment and information in multi-period insurance contracting: A comprehensive review and new empirical evidence

Abstract The central question in multi-period insurance contracting is the type of inter-temporal pricing pattern. Some products have a highballing (front-loaded) pattern, others are lowballing (back-loaded), and still others are flat. These patterns are sensitive to commitment and informational conditions of insurance products. This paper presents the first comprehensive review of theoretical and empirical research to uncover the roles of commitment and information in determining the type of inter-temporal pricing pattern. Moreover, a new two-sample empirical design is constructed, which excludes heterogeneity in firms, markets, and time periods, thus to isolate the impact of insurer's commitment on its inter-temporal pricing strategy. Insurer learning is also a necessary informational condition for a lowballing pricing strategy; however whether the learning is asymmetric or symmetric turns out to be irrelevant. The paper emphasizes the control of insurance demand and supply factors in addition to the risk type when empirically examining the risk-based dynamic selection.

Keywords Inter-temporal pricing strategy · Risk-based dynamic selection · Repeated (dynamic) contracting · Competitive equilibrium · Insurer learning

JEL Classification G22 · D82 · D83

1 Introduction

Multi-period insurance relationship is appreciated by both the insured and the insurer. The insured is willing to pay more for long-term fixed-price coverage (Kunreuther and Michel-Kerjan, 2015); and the insurer is willing to supply more comprehensive coverage if long-term insurance relationship is sustainable[1] (Crocker and Moran, 2003). Multi-period insurance contracting is also economically relevant given that the majority of insurance products, either long-term or short-term with renewals, involve a multi-period relationship.[2] However, the dynamic nature of such multi-period insurance contracting increases the difficulties of theoretical modelling and empirical testing. This paper advances the multi-period insurance contracting research by providing a comprehensive review and by presenting new empirical evidence.

Academic research on multi-period insurance contracting, particularly in a competitive setup, emerged much later than that on single-period contracting. The seminal models of Kunreuther and Pauly (1985, hereafter KP), Palfrey and Spatt (1985, hereafter PS), and Cooper and Hayes (1987, hereafter CH) yield different predictions on multi-period competitive equilibriums, inter-temporal pricing (profit) patterns, and portfolio risk dynamics. These predictions are sensitive to the following informational and commitment conditions (de Garidel-Thoron, 2005): (1) the information symmetry assumption between insured and insurer(s), and between incumbent insurer and competing insurers; (2) the commitment assumption to multi-period insurance relationship from the insurer(s) and from the insured. This paper reviews 15 theoretical works in competitive multi-period insurance contracting aiming to construct a common theoretical platform (see Table 1) and to compare the roles of information and commitment conditions in respective multi-period insurance contracting predictions.

The differences in theoretical predictions particularly concern with the inter-temporal pricing strategy of highballing (front-loaded) or lowballing (back-loaded)[3] (D'Arcy and Doherty, 1990), and the inter-temporal risk-based dynamic selection, i.e., high- or low-risk departures over time (Finkelstein, McGarry, and Sufi, 2005). Empirical research thus emerged to discriminate different theoretical predictions. This paper reviews 11 empirical works in multi-period insurance contracting aiming to isolate the roles of commitment and information in determining the inter-temporal pricing strategy and the risk-based dynamic selection.

A major deficiency of the synthesis approach is that it does not always compare apples with apples. The comparison conclusions from the existing empirical research are based on different insurers, different markets, and different time periods. Thus, it is not yet known whether the different pricing and risk selection patterns result from the strategic decision based on commitment and information conditions of different products, or simply from other characteristic differences among insurers, markets, and/or time periods. To complement this deficiency, the paper presents a pair of two samples from the same insurance company, the same market, and almost the same time period. The key difference in the two insurance products is whether the insurer is pre-committed to the long-term insurance relationship. This unique empirical design isolates the impact of the insurer's commitment from other factors impacting the pricing strategy choice (e.g., business targets, management preferences) and thus strengthens the causal link between the insurer's commitment and highballing pricing strategy, and between the lack of insurer's commitment and lowballing pricing strategy. Moreover, this new evidence

[1] In some markets, for example, Swiss insurers usually give a premium discount for insureds that accept three- or five-year contracts, which indicates a strong preference in long-term coverage.

[2] It is rather uncommon to see single-period insurance relationships. Even for single project-based coverage, such as construction all risks or satellite launch protection, the project coverage is usually embedded in a multi-period insurance relationship between the insured and the insurer.

[3] The highballing (lowballing) pricing strategy means that the insurer charges higher (lower) premium in early periods of the multi-period contractual relationship and charges lower (higher) premiums in later periods. The high or low premiums are measured relative to the actuarial fair premiums.

shows that the insurer learning is a necessary condition for the lowballing pricing strategy in a no commitment environment (Cohen, 2012), though whether the learning is asymmetric or symmetric turns out to be irrelevant.

This paper contributes to the multi-period insurance contracting research in two ways. It presents the first piece of comprehensive review mapping empirical evidence with theoretical models (see Table 1). This synthesized theoretical platform clarifies the roles of commitment and information in determining the inter-temporal pricing strategy and the risk-based dynamic selection, and thus provide theoretical structure for future empirical research. In addition, it constructs a two-sample empirical test, which precludes heterogeneity in firms, markets, and time periods, and thus improves the credibility of insurer's commitment-pricing strategy relationship. The results expand the empirical evidence on insurer learning (Hendel and Lizzeri, 2003; Cohen 2012) and insurance commitment (Dionne and Doherty, 1994; de Garidel-Thoron, 2005). The paper also provides practical implications on insurance product management, which may serve as a basis for pricing strategy decisions.

The remainder of the paper is structured as follows. Section 2 constructs the common theoretical platform based on synthesis and comparison of extant theoretical models. Section 3 derives the hypotheses. Section 4 compares extant empirical evidence and concludes the roles of commitment and information in pricing strategy based on extant empirical evidence. Section 5 presents the two-sample empirical design, and reports the results. Section 6 concludes.

2 Common theoretical platform

The multi-period insurance contracting models are traceable to, among others, contract theories in labor (Harris and Holmstrom, 1982), procurement (Laffont and Tirole, 1990), and credit (Sharpe, 1990) markets. The development of contract theory leads modern insurance economics in three directions (D'Arcy and Doherty, 1990; Chiappori and Salanie, 2013). The first is the single-period contracting in competitive insurance markets, where Rothschild and Stiglitz (1976, hereafter RS) derive a separating equilibrium with different contracts for high and low risks respectively under adverse selection. Alternatively, Miyazaki (1977), Wilson (1977), and Spence (1978) demonstrate the possibility of a pooling equilibrium. The second direction is the multi-period contracting in a monopoly insurance market, where the role of experience rating is highlighted to solve the problem of adverse selection (Dionne, 1983; Dionne and Lasserre, 1985, 1987; Hosios and Peters, 1989). The third and the most recent direction is the multi-period insurance contracting in competitive markets, on which this paper will focus.

The contract(s) at the multi-period equilibrium is characterized under various commitment and informational assumptions. There are three types of commitment assumption: (1) no commitment, where neither the insurer nor the insured pre-commits to a multi-period insurance relationship; (2) semi-commitment, where the insurer pre-commits[4] to a multi-period insurance relationship but the insured does not; and (3) full commitment, where both the insurer and the insured pre-commit to a multi-period insurance relationship at the beginning of the first period (Dionne and Doherty, 1994).[5] The typical form of no commitment is the annual contract (e.g., automobile insurance), which is renewable but without renewal guarantee from either side. The typical forms of semi-commitment include long-term contract (e.g., ten-year term life) and annual contract with guaranteed renewability (e.g., individual health insurance with guaranteed renewal clause). It is possible but uncommon to see full commitment insurance contracts, because insurance law in most markets allows the insured to cancel the insurance

[4] In practice, the insurer's commitment has multiple forms, e.g., long term contracts (term life) or guaranteed renewability (health insurance). One of the common features of these commitments is the commitment to a pre-agreed premium schedule, which can either be contingent or non-contingent on claim experience.

[5] It is rarely seen in the insurance market that the insured is bound to a multi-period relationship with an insurer, while the insurer is not (Dionne and Doherty, 1994).

policy at any time. However, the insured can partially commit due to relationships other than insurance. For example, the employment relationship partially binds the insured to the employer sponsored group health insurance; the mortgage relationship partially binds the insured to the mortgage life insurance.

The informational assumptions in multi-period insurance contracting involve two layers: between the insured and the insurer(s) and between the incumbent (current) insurer and the competing (rival) insurers. The first layer has been extensively investigated in the single-period setup, within the context of adverse selection and moral hazard. The second issue has recently emerged from the multi-period setup: the incumbent insurer may obtain information advantages to its competitors, due to its learning[6] from the contractual experience with the insured. Pauly (2003) constructs three information structures concerning the insured's risk type,[7] based on the two layers of informational assumptions: (1) classic adverse selection, where the insured has private information that none of the insurers knows; (2) symmetric information, where the insured and all insurers have common knowledge at every point in time; (3) asymmetric learning, where the insured and the incumbent insurer have common knowledge at every point in time but the competing insurers do not. This paper further develops Pauly's (2003) information structures to five categories based on whether adverse selection is present in the first (early) period of contract and on the learning types in the second (later) period (asymmetric, symmetric, or no learning)[8].

Table 1 structures the theoretical framework of multi-period insurance contracting in 15 assumption sub-categories by three commitment types and five risk information structures. The sub-category of full commitment and no learning is essentially single-period contracting because no change can happen across periods. All models are discussed in a two-period setup, where the long-term contract has a duration of two periods, and the short-term contract has a duration of one period. They are structured in three panels subject to whether adverse selection[9] is present in period 1.

Three theoretical predictions, where available, are discussed, under each assumption sub-category. The first is the multi-period equilibrium, with a focus on whether separating contracts are offered to high and low risks or one pooling contract is offered to all risks. Second, a competitive market implies zero-profit contracts over multiple periods at the equilibrium (KP, 1985; CH, 1987). Thus, inter-temporal subsidization between young and old policies may exist in order to reach the multi-period zero-profit equilibrium.[10] Thus, an inter-temporal pricing or profit pattern at the multi-period equilibrium may exist, i.e. whether young policies subsidize old policies (front-loaded, highballing), old policies subsidize young policies (back-loaded, lowballing), or no inter-temporal subsidization (actuarially-based, flat). The third prediction is on risk-based dynamic movements, i.e. if high or low risks systemically depart from the insurance portfolio in period 2.

[6] Learning reflects the updates in part the initial (but unknown) differences in risks, and in part the signal (and real) changes in risks (Pauly, 2003).

[7] There are multi-dimensions in the insured's risk information, e.g., the risk attitude, which also have an impact on insurance contracting (Finkelstein and McGarry, 2006). However, all models discussed in this paper (implicitly) assume the risk type as the only dimension of risk information.

[8] The scenario of no adverse selection and no learning is omitted, because it degenerates to general contracting theory and thus is not particularly interesting to insurance contracting studies.

[9] All models discussed in this paper (implicitly) assume no moral hazard. A separate stream of multi-period contracting studies considering moral hazard can be found in e.g., Rubinstein and Yaari (1983) and Rogerson (1985).

[10] All models discussed in this paper (implicitly) assume no cross subsidization among multiple products for one insured, and assume exclusive contract(s), i.e. the insured buys one type of coverage from only one insurer. The cross-subsidization between high and low risks in a multi-period setup is investigated by e.g. Ma and Browne (2005).

Table 1 Theoretical framework of multi-period insurance contracting

Commitment / Insurer learning	No commitment	Semi-commitment (One-side commitment)	Full commitment (Two-side commitment)
Panel A: Adverse selection is present in period 1			
Asymmetric learning	Pooling in period 1, separating in period 2, lowballing, high risks tend to departure (KP, 1985; Nilssen, 2000).	Separating; low risks choose highballing long-term contract, high risks tend to departure from the long-term contract and to choose repeated short-term contract (CH, 1987). Semi-pooling in period 1 and separating in period 2; low risks choose highballing long-term contract; high risks tend to departure from the long-term contract (Dionne and Doherty, 1994).	Separating; policies for high risks degenerate to single-period; policies for low risks are experience rated with flat pricing pattern (CH, 1987).
Symmetric learning	Pooling or semi-pooling, flat, no systemic departure (Watt and Vazquez, 1997).	Not yet covered by literature	Not yet covered by literature (see footnote 12)
No learning	Separating, flat, no systemic departure (Vazquez and Watt, 1999).	Separating, flat, no systemic departure (Vazquez and Watt, 1999).	Separating, flat (RS, 1976). Pooling, flat (Miyazaki, 1977; Wilson, 1977; Spence, 1978).
Panel B: Adverse selection is NOT present in period 1			
Asymmetric learning	Pooling in period 1, lowballing, high risks tend to departure (de Garidel-Thoron, 2005).	Pooling, flat, high risks tend to departure (de Garidel-Thoron, 2005).	Not yet covered by literature
Symmetric learning	Pooling, flat, no systemic departure (PS, 1985; Prendergast, 1992; Cochrane, 1995).	Pooling, highballing, low risks tend to departure (PKH, 1995; HL, 2003). Separating, undetermined pricing and risk departure pattern (Crocker and Moran, 2003).	Pooling, undetermined pricing pattern (Crocker and Moran, 2003).
Panel C: Theories connecting panel A and B			
Three scenarios (Pauly, 2003) Pooling, highballing, undetermined risk departure pattern (Pauly, Menzel, Kunreuther, and Hirth, 2011)			

2.1 Panel A: Adverse selection is present in period 1

CH (1987) and KP (1985) initiate the modelling of multi-period contracting in the insurance context, where adverse selection is an important feature.

Assuming no commitment, KP (1985) and Nilssen (2000) model the scenario of asymmetric insurer learning; Watt and Vazquez (1997) model symmetric learning; and Vazquez and Watt (1999) describe no learning. KP (1985) predict a pooling equilibrium in period 1, as that the insurer offers one type of short-term contract to all risks at the price reflecting the average of low and high risks in period 1. In period 2, risks who had claim(s) in period 1 (high risks), switch to competing insurers. This is because the incumbent insurer can increase the premium for the period-1 claimant; however, the competing insurers cannot tell who had a claim in period 1. Risks who did not have a claim (low risks) stay with the incumbent insurer, since the incumbent insurer shall keep their premium unchanged thus they are indifferent to switch or stay. Therefore, in period 2, the insurer can earn a positive profit by over charging the staying (low) risks. Under the zero-profit constraint, the insurer must price lower than zero-profit in period 1 to attract new customers, which is considered as the cost of acquiring knowledge about the insured's risk type. The incumbent insurer earns an informational (monopoly) quasi rent in period 2, which competing insurers do not. This pricing and profit pattern for a sequence of short-term contracts are thus lowballing. The risk-based dynamic selection pattern is thus the high-risk departure and the low-risk locked in. Nilssen (2000) addresses two challenges to KP's (1985) predictions. First, KP (1985) assume a myopic insured, who only considers the payoffs in period 1, but not in period 2, when making the initial decision. Nilssen's (2000) conclusion is free of this assumption. Second, Nilssen (2000) extends RS's (1976) and CH's (1987) classical model, thus responding to concerns on KP's (1985) modelling. His predictions are largely consistent with KP's (1985) as that a pooling equilibrium is more likely to happen than the separate equilibrium, a lowballing pricing pattern prevails, and the low risks are locked in.

Watt and Vazquez (1997) assume that all insurers learn the insured's risk type at the beginning of period 2, and thus adverse selection is only present in period 1. They prove a pooling equilibrium of full coverage if low risks are patient enough; or a semi-pooling equilibrium, where a portion of impatient low risks choose a sequence of RS's (1976) partial coverages and all high risks and patient low risks choose a sequence of full coverages. At equilibrium, no inter-temporal subsidization is inferred, since in period 1, the insurer undercharges high risks but overcharges low risks, thus expects a zero-profit; in period 2, full information contracts are in place and thus all risks are charged at an actuarially fair rate. Vazquez and Watt (1999) assume no insurer learning over time. The model is a straightforward extension of RS's (1976) to a multi-period setting. They conclude that the multi-period equilibrium must be a periodic repetition of RS's single-period separating equilibrium. The high risks are offered with a sequence of full coverages and low risks partial coverages. Thus the profit of each period is zero and no inter-temporal subsidy is allowed.

Assuming semi- and/or full commitment, CH (1987) and Dionne and Doherty (1994) model the scenario of asymmetric insurer learning; Vazquez and Watt (1999) discuss no learning; the scenario of symmetric insurer learning has not yet been covered by literature.[11] CH (1987) extend RS's (1976) single-period adverse selection model to multi-periods and discuss both semi- and full- commitment scenarios. Semi-commitment yields a separating equilibrium, as the insurer offers experience rated long- and short-term contracts; high risks choose the repeated short-term contracts; low risks choose the long-term contract. The dynamic behavior of insurance rates is described, as that in period 1, the insurer

[11] If full commitment, the asymmetric and symmetric learning maybe indifferent, because both parties pre-commit to a long-term contract and thus competition among insurers does not exist in period 2. Thus whether the insurer learning is asymmetric or symmetric makes no difference.

charges low risks a higher premium than they should pay in a standard one-period contract; in period 2, the insurer gives those low risks without any period 1 claim a heavy discount, and thus charges them a lower premium than they should pay in a standard one-period contract. That is to say the pricing and profit pattern for the experience rated long-term contract is highballing. The insurer tilts payoffs towards the future to provide an incentive for insureds to remain with the firm. Full commitment yields another separating multi-period equilibrium as the insurer offers both experience rated and non-experience rated long-term contracts. High risks choose non-experience rated long-term contract, which is equivalent to a single-period contract. Low risks choose experience rated long-term contract,[12] which is actuarially fair at each period, i.e. a flat pricing pattern.

Dionne and Doherty (1994) extend the semi-commitment modelling with renegotiation, which allows the insurer initially to commit to a long-term contract and to offer a revised short-term contract in period 2. The insured may stick to the long-term contract, accept the revised second-period short-term contract, or switch insurer in period 2. They conclude that the equilibrium is semi-pooling in period 1, where a portion of high risks chooses short-term full coverage, and the rest of high risks and all low risks choose long-term partial coverage. The equilibrium is separating in period 2, where high risks change to short-term full coverage (either offered by the incumbent insurer as the renegotiation or by a competing insurer); low risks stay with the long-term partial coverage. The equilibrium is similar to CH's (1987) and is characterized by positive first-period expected profits and negative second-period expected profits for low risks, i.e. price highballing.

Vazquez and Watt (1999) discuss the scenario of no insurer learning and conclude that "if commitment were a possibility, it is really just a redefinition of the term 'period'. … Hence, multi-period contracts with commitment can be thought of as single-period contracts and so initial type revelation is possible, as was initially shown by Rothschild and Stiglitz (1976)."

2.2 Panel B: No adverse selection in period 1

Assuming no commitment, PS (1985), Prendergast (1992), and Cochrane (1995) model the multi-period insurance contracting with symmetric learning;[13] de Garidel-Thoron (2005) covers the scenario of asymmetric learning. PS (1985) predict that the equilibrium is pooled since there is no adverse selection in both periods. All policies are experience rated in period 2, based on the symmetric learning from the claims reported in period 1. The short-term policy in each period has a zero profit, implying a flat pricing pattern. This is because in period 1, no one knows the risk type, thus only a pooled premium for an average risk can be charged; in period 2, all insurers and the insured know the risk type, all risks will be charged with actuarially fair premium.

Prendergast (1992) develops a model based on Wilson's (1977) game form. Unlike PS (1985), Prendergast (1992) assumes that the insured's non-reported accidents[14] in period 1 constitute his/her private knowledge in period 2, which no insurers would know, i.e. adverse selection is present in period 2. He proves a pooled equilibrium with small-deductible partial insurance in both periods, which relies on the asymmetric information assumption in period 2. He argues that the insurer(s) shall never offer contract to pay small losses in period 1, thus to reduce the incentive of insured's not-to-report claims; and as long as the deductible is small enough, neither the incumbent insurer nor the competing insurers shall offer a RS's (1976) menu contracts, but offer the partial insurance as in period 1. No inter-temporal subsidy is implied at his equilibrium.

[12] In practice, this could be a long-term contract with a pre-agreed premium schedule/tariff contingent on the policy loss experience.

[13] In this case, all parties (insured, incumbent insurer, and competing insurers) share common information at every point in time.

[14] The insureds tend not to report small accidents in period 1, since they want to establish a reputation as low risks, so that they can get a better term in period 2.

Cochrane (1995) focuses on how to design a scheme that motivates the insurer's commitment to offer long-term health coverage (endogenous commitment). He proves a pooled equilibrium for standard short-term health insurance with flat pricing pattern and with no insured lock-in effect. He proposes a separate coverage or separate policy accompanying by the short-term standard health insurance to insure the insured's reclassification risk,[15] which provides a lump-sum insurance payment equal to the current value of future health premium increases due to risk type changes, for example, worsening health condition. This time-consistent health package enables the insurer to offer and the insured to afford health coverage at all periods at an actuarially fair premium, even if it is expensive in later periods. In other words, the insurer endogenously commits to a long-term contractual relationship with the insured, while the insured keeps his/her flexibility to switch insurers.

De Garidel-Thoron (2005) extends the modelling from symmetric to asymmetric learning by assuming that both the insured and the incumbent insurer learn about the insured's risk type during period 1, but competing insurers do not. Thus adverse selection arises in period 2 between the insured and competing insurers. The commitment of both insured and insurer is assumed to be endogenous, i.e. no *ex ante* commitment. He predicts that both the insured and the insurer may generate some commitment endogenously, the insurer will not exercise the right to modify or withdraw the contract, and thus long-term contractual relationship is the unique equilibrium. He also predicts a lowballing pricing pattern, a lock-in effect for low risks, and a tendency that high risks departure from the long-term contract to seek cheaper non-experience rated second period offer.

Assuming semi- and/or full commitment, Pauly, Kunreuther, and Hirth (1995, hereafter PKH), Hendel and Lizzeri (2003, hereafter HL), and Crocker and Moran (2003) develop models assuming symmetric learning; de Garidel Thoron (2005) covers the scenario of asymmetric learning. PKH (1995) assume that the insurer pre-commits to the long-term contractual relationship by offering guaranteed renewability[16] in a sequence of short-term policies. They prove a pooled equilibrium and a highballing premium pattern. The insurer charges all risks higher than fair premium in period 1, to cover the future reclassification risk and to lock in low risks. Though the insured is legally allowed to cancel the contract, he/she would not since he/she would lose the part of front-loaded premium covering reclassification risk. PKH (1995) and Pauly, Nickel, and Kunreuther (1998) acknowledge the possibility of a level, instead of a declining, actual premium across-periods in reality, which also reflects the highballing pattern, because the health risk increases over time and thus the level premium declines relative to the risk and to the actuarially fair premium.

HL (2003) follow the same assumption as PKH (1995) and derive an equilibrium that is pooled for high and low risks, but separating for different insureds' preference concerning the tradeoff between the level of front-loading and the degree of reclassification risk protection. That is to say some risks choose more front-loaded contract (e.g., level premium term life), and thus obtain full protection of reclassification risk; others choose a less front-loaded contract (e.g., annual renewable term life with premiums that depend on age and time elapsed since last medical examination), and thus bear some reclassification risk themselves. The pricing pattern is highballing, which is an important device to lock in low risks. The model implies that low risks tend to departure from the incumbent insurer.

Crocker and Moran (2003) develop a model focusing on the relationship between the coverage and the insured's commitment. They introduce an indicator of job switching cost to capture the insured's commitment in the group health insurance and thus to cover the spectrum from semi-commitment to full commitment, including the insured's partial commitment. The insurer's ability to offer long-term

[15] Alternative terms are insurability risk, re-underwriting risk, renewability risk (Fei, Fluet, and Schlesinger, 2015), and premium risk (Pauly, 2003). Reclassification risk refers to the insured's risk is reclassified in later periods resulting in a significant increase of premium at policy renewals.

[16] The guaranteed renewability does not only guarantee renewals but also guarantee to only change premium to the same extent for all in the initial rating class (community rating) or following a pre-agreed premium schedule in subsequent periods (contingent rate).

contract or to cover reclassification risk is endogenous and depends the insured's level of commitment. They prove a pooled equilibrium subject to a certain threshold of insured's commitment. Along with the increase of insured's commitment, the partial coverage gradually converges to full coverage. RS's (1976) separating equilibrium is also viable when the level of commitment is below the threshold. The inter-temporal pricing is not incorporated in their model.

De Garidel-Thoron (2005) compares the semi-commitment with no commitment scenario. He predicts that if the insurer could commit to a long-term contract, the equilibrium will be pooled long-term contracts with bonus-malus type of experience rating. The low-risk insureds are locked in, as the competing insurers cannot offer them a fair premium in period 2 due to lack of information. A flat pricing pattern is implied. De Garidel-Thoron (2005) emphasizes that the asymmetric learning, where no information sharing among insurers is enforced, is strictly better off than the symmetric learning, independent of the insurer's ability to offer long-term contract. This is because the asymmetric information between incumbent and competing insurers weakens the competing insurer's ability to exercise a cream-off strategy, and thus improves the long-term commitment of both parties, the benefits of which outweigh the welfare loss due to asymmetric information.

2.3 Panel C: Theories connecting panel A and B

Pauly (2003) discusses three scenarios. First, he takes de Garidel-Thoron's (2005) no commitment scenario and concludes a pooling equilibrium in period 1, lowballing pricing pattern, lock-in effects for low risks, and implying a high-risk departure pattern. Second, he discusses the semi-commitment scenario in PKH (1995) and HL (2003). A pooled equilibrium with price highballing and low-risk lock-in can be expected, implying a low-risk denaturing pattern. Third, he attempts to build the connection between the adverse selection and no adverse selection models. He argues that the presence of adverse selection (in period 1) should not change the highballing implication embedded in the insurer's commitment (guaranteed renewability). This third aspect is formalized by Pauly, Menzel, Kunreuther, and Hirth (2011, hereafter PMKH).

PMKH's (2011) model reconciles models assuming adverse selection with those assuming no adverse selection in period 1, and thus bridges the two panels of models in multi-period insurance contracting. They extend PKH's (1995) model to allow for adverse selection in period 1 and asymmetric learning in later periods. They prove a "pseudo-pooled" equilibrium with guaranteed renewal contracts of each period, which is essentially the same as PKH's (1995). The highballing pricing pattern remains. They argue that the incumbent insurer cannot take their information advantages to charge higher than fair premium for low risks in period 2, because it charges high front loading from all risks in period 1 and subjects to the zero-profit constraint. This prediction is against KP's (1985) and de Garidel-Thoron's (2005) intuition, where the incumbent insurer asymmetrically learns risk information and thus is able to systemically over charge low risks in period 2. They also discuss the potential connections with CH's (1987) scenario, where the experience rating based on individual claim experience is allowed. They argue that such experience rating would violate the explicitly promise inherent in guaranteed renewability, thus prospective new purchasers would punish such skimping insurers by refusing to buy.

The theoretical framework in Table 1 suggests three trends: (1) no commitment associates with lowballing and semi-commitment with highballing pricing strategy; (2) adverse selection associates with a separating equilibrium; and (3) asymmetric learning associated with high-risk departure pattern. Theoretical researchers have tried to prove the existence of such trends, particularly concerning the commitment-pricing strategy relationship. For example, Dionne and Doherty's (1994) and HL (2003) point out the commitment sensitive nature of an insurer's pricing strategy. PMKH (2011) prove that the pricing strategy is independent of the information structure, under semi-commitment terms. These trends yield testable hypotheses and call for empirical investigations.

3 Hypotheses

The theoretical framework in Table 1 suggests that for the no commitment scenario, the pricing patterns are either lowballing or flat; for the semi-commitment scenario (including semi-commitment with renegotiation), the pricing patterns are either highballing or flat. Theoretical predictions also diverge in risk-based dynamic selection, i.e., whether high or low risks tend to departure in period 2. The theories yield two pairs of hypotheses as presented in table 2. The choice for the null hypothesis follows the "prediction tendency" summarized in Table 1 and the common practice in existing empirical research.

The intuitions are as follows. Under the no commitment scenario, the insurer uses low price to attract new clients and earns an informational quasi rent so that it can discriminate high and low risks, while the competing insurers cannot. This is termed "information monopoly rent" in economics. Thus, high risks tend to leave the incumbent insurer because he/she will be perceived as an average risk by competing insurers (KP, 1985; Nilssen, 2000). Under semi-commitment scenario, the insurer and the insured pre-agree on a premium structure at the beginning of the multi-period contractual relationship. The insured's risk type develops over time or the insurer and the insured gradually learn more about the risk type. Therefore, low risks tend to depart from the incumbent insurers in search of a better premium structure when they become aware that they are low risks, because the current premium structure was agreed based on the expected risk, a mixture of high and low risks, some years ago. High risks would have no incentive to select themselves out of the original premium structure. The price highballing strategy is thus implemented with the pre-agreed premium structure aiming to lock in low risks, which, however, might not be sufficient to eliminate the low-risk departure pattern (HL, 2003; Finkelstein, McGarry, and Sufi, 2005). A renegotiation strategy may also play a role when the incumbent insurer wants to retain low risks based on its newly learned information (Dionne and Doherty, 1994).

Table 2 Hypotheses

	Commitment Assumption	Null Hypotheses (H0)	Alternative Hypotheses (H1)
H1	*The inter-temporal pricing pattern is*		
H1A	no commitment	lowballing	Flat
H1B	semi-commitment	highballing	Flat
H2	*The inter-temporal risk departure pattern is*		
H2A	no commitment	high risks departure	no pattern
H2B	semi-commitment	low risks departure	high risks departure or no pattern

The winner's curse in the banking industry is similar to the risk-based dynamic selection problem in the insurance context. The winner's curse results from the ability of rejected loan applicants to apply at additional banks (Shaffer, 1998) and thus the competing banks are more likely to attract higher-risk applicants. Similar to the high-risk departure pattern in H2A, the winner's curse problem results from the asymmetric information between the incumbent bank (insurer) and its competitors (Sharpe, 1990). The incumbent bank (insurer) earns an informational monopoly quasi rent over its competitors and thus is able to select low risks.

Table 3 Empirical evidence in multi-period insurance contracting

	D'Arcy and Doherty (1990)	Cohen (2012)	Kofman and Nini (2013)	Shi and Zhang (2015)	Dionne and Doherty (1994)	Hendel and Lizzeri (2003)	Cox and Ge (2004)	Finkelstein, McGarry, & Sufi (2005)	Herring and Pauly (2006)	Pinquet, Guillen, and Ayuso (2011)	Hofmann and Browne (2013)
	No Commitment				*Semi-Commitment*						
Product	Auto	Auto	Auto	Auto	Auto Liability	Term Life	LTC	LTC	Individual Health	health, life, and LTC	Individual Health
Market	US	Israel	Australia	Singapore	CA, US	US	US	US	US	Spain	Germany
Policy Duration	ST	ST	ST	ST	LT	LT or GR	GR	GR or LT	GR	GR	LT or GR
Commitment Type	No	No	No	No	Semi (with renegotiation)	Semi	Semi	Semi	Semi	Semi	Semi
Adverse Selection	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Insurer Learning	Asym	Asym	Sym	Btw asym and sym	Asym	Sym	Not discussed	Not discussed	Not discussed	Sym	Sym
H1A	Confirm	Confirm	Confirm	Confirm	/	/	/	/	/	/	/
H1B	/	/	/	/	Confirm	Confirm	Reject, lowballing	Confirm	Confirm	Confirm	Confirm
H2A	/	Confirm	Confirm	Confirm	/	/	/	/	/	/	/
H2B	/	/	/	/	Rejected, high risks departure	/	/	Confirm	/	Confirm	Confirm

4 Empirical evidence

It is ultimately an empirical task to determine what kind of product market matches with what kind of pricing strategy and of risk departure pattern, and to discriminate the roles of commitment and information structure (PK, 1985; Pauly, 2003). Policy makers and managers in insurance companies should rely not only on the theoretical research, but also on empirical analyses to develop their policy against competing insurers (Cohen and Siegelman, 2010). The extant empirical evidence concerning the two pairs of hypotheses is compared with the structure in Table 3 and reviewed in detail according to their different commitment types.

4.1 No commitment evidence

D'Arcy and Doherty (1990) start the empirical investigation in multi-period insurance contracting. They present the aggregate loss ratios by policy age cohorts of automobile insurance from seven US insurers. All seven portfolios show that loss ratios decline almost monotonically with policy age, suggesting lowballing pricing pattern and supporting H1A. They also look at three new market entrants, which have only new policies, but no private information. They found that these three new insurers' loss ratios were indeed high (low profit) in the beginning but gradually converge to other matured firms, supporting the price lowballing pattern in H1A.

Cohen (2012) presents the first policy-level analysis for repeated short-term insurance contracting using an Israel automobile insurance portfolio. During the entire sample period, the information-sharing platform among insurers is not available, thus the asymmetric learning best captures the nature of the market. He shows that (1) profits from repeat insureds are higher than those from new insureds (i.e. a lowballing pattern); (2) the insurer reduces the price charged to repeated insureds with good claim history by less than the reduction in expected costs associated with such insureds (i.e. premium downward stickiness); (3) repeat insureds with bad claim history are more likely to switch to other insurers (i.e. high risks departure). The evidence is obtained after controlling for all risk classification factors. It directly supports H1A and H2A. Cohen's (2012) sample matches KP's (1985) and Nilssen's (2000) assumptions and he argues for the role of asymmetric learning in determining the lowballing pricing strategy.

Kofman and Nini (2013) examine the Australian automobile insurance market, where a claim information sharing platform is in place to support a bonus-malus rating system. They believe that the publicly available data in Australian system capture all relevant risk type information about policyholders, with the only exception of brand new policies. Thus the market matches with Watt and Vazquez's (1997) assumptions, (i.e. adverse selection in period 1, symmetric learning in later periods, and no commitment). The public nature of such system eliminates one important source of asymmetric learning. They document evidence of both lowballing pattern and high risks departure, supporting H1A and H2A. Their evidence challenges Cohen's (2012) argument regarding the important role of asymmetric learning in determining product pricing strategy.

Shi and Zhang (2015) investigate an insurer learning scenario in between Cohen's (2012) no information sharing market and Kofman and Nini's (2013) complete information sharing market. The Singapore automobile insurance market has a no-claim-discount (NCD) system and a public information sharing platform. However, the platform contains only information regarding the NCD status but neither the insureds' claim history nor their policy choice, which implies a partial information sharing among insurers (Shi and Zhang, 2015). Their conclusions again support H1A and H2A and suggest the product pricing strategy may not depend on insurer's learning type.

4.2 Semi-commitment evidence

Dionne and Doherty (1994) examine a special automobile liability insurance portfolio from California, where two types of policies are offered: a long-term policy (semi-commitment with renegotiation) and a short-term policy (no commitment). They approximate the average policy age in a portfolio by the premium growth of that portfolio (i.e. high (low) growth indicates in average younger (old) policy age) and find a positive correlation between average policy age and loss ratio in the subsample of low risks, which is in line with the highballing prediction of semi-commitment (with renegotiation) model and thus supports H1B. Such a highballing pattern is not found in intermediate- and high-risk groups, suggesting that only the low risks choose semi-commitment long-term policies, and high risks choose flat rated short-term policies. This is in line with CH's (1987) prediction and does not support the null but the alternative hypothesis of H2B, i.e. high risks departure.

HL (2003) present the first-piece of evidence controlling for underlying risk differences, i.e. risk classification, in multi-period insurance contracting. They look at three products of life insurance from 55 US life insurers: 20-year term life with level premium each year (TL), annual renewable term life with premiums that depend only on age (ART), and annual renewable term life with premiums that depend on age and time elapsed since last medical examination (Selection & Ultimate ART). They find that TL and ART are significant front-loaded, where the insurer pre-commits to a long-term contract (LT) or to the guaranteed renewability with a determined rating schedule (ART). The relative price to the risk almost monotonically decreases through the 20 years, supporting H1B. However, for Selection & Ultimate ART, where the premiums in later periods depend on whether the insured passed the medical reexamination (a weakened commitment with re-underwriting elements), the front-loading exists only in the first year but not in following years. They approximate the risk by the present values of premiums and find negative correlation between the front-loading and the risk: more front-loaded contracts insure higher proportion of low risks. They also show that more front-loaded contract (LT) has a lower lapse rate than less front-loaded contract (ART), indicating the low-risk lock-in effects associate with the highballing pricing strategy. Unfortunately, HL (2003) are not able to directly test the risk departure dynamics, which is then complemented by Finkelstein, McGarry, and Sufi (2005).

Cox and Ge (2004) present a panel data from the US long term care (LTC) insurance market and with cohort-specific information. They find a positive correlation between policy age and loss ratio, but argue that it reflects the risk changes over time and thus not a price highballing strategy. They also find a negative correlation between the square of policy age and loss ratio, and argue that it indicates a decreasing speed of loss ratio increases and thus indicates the insurer gradually increase the price relative to actuarial fair premium (i.e. a price lowballing strategy).

One way to solve this apparent theoretical (highballing, H1B) and empirical (lowballing in Cox and Ge, 2004) contradictory is to use the policy level data and control for risk classification, so that the coefficient between policy age and price/profit can directly reveal the pricing pattern. Finkelstein et al. (2005) examine the US long-term care market in such a direct way. They document pricing highballing evidence consistent with HL (2003) from the US life market, thus supporting H1B. Moreover, they examine the risk departure dynamics using the policy-year-level data controlling for risk classification. They show that insureds who let their policies lapse are indeed lower risks than those who stay. It directly supports H2B and is exactly what HL (2003) predict.

Herring and Pauly (2006) numerically develop an ideal/optimal incentive compatible premium schedule for individual health insurance with guaranteed renewability, based on PKH's (1995) semi-commitment model. In addition, they estimate the actual market premiums for individual health insurance using Medical Expenditure Panel Survey, Community Tracking Study Household Survey, and National Health Interview Survey. They find that the actual premium schedule "does appear to be surprising consistency" with the estimated ideal premium schedule, thus supporting the highballing prediction in H1B. They conclude that the front-loaded premium is necessary for health insurers to provide a guaranteed renewability and to insure the reclassification risk, however, is mitigated because the low-risk's expected expense increases with age, the likelihood of becoming a high-risk increases with age, and the high risk either recovers or dies.

Pinquet, Guillen, and Ayuso (2011) examine the dynamic lapse (departure) behavior in a long term package coverages of health, life, and LTC from the Spanish market. Premiums are paid annually. The experience rating on individual basis is not allowed. They find front-loaded pricing strategy (H1B) in all three coverages evidenced by the increased benefit ratios from younger to older groups. Moreover, they observe a continuously decreased lapse rate over insured's age with an exception at age 65. They explain that the cost of lapse increases with the policy age and younger policyholders usually have a small policy age. Hence, younger policyholders are less locked in by the front-loading if they want to lapse for whatever reason. This result supports H2B in the sense that younger policyholders (low risks) tend to departure from the portfolio. They also discuss other possible explanations for the risk dynamics, e.g., the insured's insufficient knowledge about insurance products, and why reclassification risk is unlikely to be a major reason for young policyholder lapse.

Hofmann and Browne (2013) present evidence from the German long-term private health insurance (semi-commitment), where the insurers commit to offer renewal at a premium rate that does not reflect revealed future information about the insured risk. They support the theoretical predictions in HL (2003): a price highballing strategy (H1B) generates the effect of insured lock-in, and a low-risk departure pattern (H2B). The evidence from the German private health market demonstrates the robustness of pricing and risk dynamic predictions, which are immunized from the strict regulation and from the existence and possible domination of social insurance program. This work also contributes to the debate how private health solutions can insure the reclassification risk. The empirical evidence shows the viability of the front-loaded premium schedule with guaranteed renewability (PKH, 1995) at least in a strictly-regulated and social insurance dominated market. In such market, the accessibility of health coverage is much less a problem than that in a private insurance driven market.

4.3 Results from synthesized evidence

Table 3 reveals the different roles of commitment and information structure in determining the inter-temporal pricing strategy. First, if the insurer offers only short-term contracts (i.e. the insurer has no commitment), the inter-temporal pricing pattern is lowballing (all four pieces of evidence support H1A); if the insurer offers long-term contracts or a sequence of short-term contracts with guaranteed renewability (i.e. the insurer commits to multi-period contractual relationship), the pattern is mostly highballing (six out of seven support H1B). The comparison results based on extant empirical evidence strongly support Dionne and Doherty's (1994) and HL's (2003) theoretical assertion that the product pricing strategy is sensitive to the commitment types.

Second, by the nature of insurance markets (Cohen and Siegelman, 2010), ten out of eleven products reviewed in this paper present some kind of adverse selection. Among the ten adverse selection cases, four present lowballing pricing pattern and six highballing. Comparing HL's (2003) evidence with Pinquet et al.'s (2011), both examine a term life coverage with guaranteed renewability and symmetric learning; both conclude the same highballing pricing pattern. However, adverse selection is not a problem in HL's (2003) portfolio; while Pinquet et al. (2011) acknowledge the presence of adverse selection. The comparison results show that the pricing pattern is insensitive to the presence or absence of adverse selection.

Third, eight out of eleven pieces of evidence specify or indicate the insurer's learning type, in which three feature asymmetric learning, four symmetric learning, and one in between. Both highballing and lowballing pattern are present in both sub-categories of asymmetric and symmetric learning. Cohen (2012), Kofman and Nini (2013), and Shi and Zhang (2015) show three automobile portfolios from three markets, which have no, full, and partial information sharing systems respectively. All three papers conclude the same lowballing pricing pattern. This is a strong signal that the pricing pattern is insensitive to insurer learning types (PMKH, 2011).[17] The roles of commitment and information in risk-based dynamic selection are discussed later.

5 New empirical evidence

A major shortcoming of the results from synthesized evidence is that it does not always compare apples with apples. The comparison conclusions are based on different insurers, different markets, and different time periods, which may blur the pattern from a product pricing strategy. For example, the appeared pattern may be driven by short-term business targets or management considerations other than a product inter-temporal pricing strategy. An insurer may be under growth pressure from shareholders in some years. A product sample from this period may yield a lowballing pricing pattern due to the target of attracting new clients; however in normal periods without particular growth pressure, such a product may be flat priced. Another example is the insurance market cycle, which reflects the long-term pricing pattern of an insurance market and is mingled with the temporal pricing pattern of a product. Thus, in order to isolate the impact of product inter-temporal pricing strategy, the hypotheses are tested with two product samples from the same insurer, the same market, and almost the same period. In such two samples, if different pricing or risk selection patterns are found, it is more convincing to conclude that the patterns result from the insurer's strategy instead of other firm-, market-, or time period-specific factors. Such an empirical design is new to multi-period insurance contracting studies and will increase the credibility of the pricing pattern found.

5.1 Samples

I obtain samples of two products from a Chinese life and health insurer. Tables 4 and 5 compare the two samples qualitatively and quantitatively. The insurer nationwide operations, with a broad spatial range that covers over 90% of the Chinese population. It is ranked among the top ten largest life insurers in China over the past 15 years in terms of premium volume and assets. Its core business comes from the open market and thus is not concentrated in any particular industry or region. Its operational model, growth path, risk portfolio, and performance are representative in the Chinese insurance market. In 2012, 68 life and health insurers and 62 property and liability insurers operated in the Chinese insurance market, and most of them are legally eligible to issue the two products considered here, yielding a very competitive market.

Sample A is a portfolio of Group Critical Illness (CI) insurance.[18] CI insurance is a type of loss-occurrence health insurance. The full insurance amount is paid as long as an insurer-recognized hospital provides the first-time diagnosis of the covered disease during the policy period. Usually, there is a 30- to 90-day waiting period for first-time purchasers. The claim benefit always equals the insurance amount and is paid to the insured in a lump sum without additional benefits, such as medical service. The claim payment does not require actual medical expenditure or hospitalization. Thus CI insurance is immunized from many common problems observed in medical expense health insurance, such as moral hazard and choices between private and public hospitals. In 2007, the Insurance Association of China and the Chinese Medical Doctor Association issued guidelines that define 25 types of critical diseases. In this case, and in most cases in the Chinese CI insurance market, the insurer strictly follows the CI coverage

[17] This observation does not necessarily mean the insurer learning is irrelevant in the multi-period insurance contracting. If no insurer learning is present, the pricing pattern may not exist. Moreover, as de Garidel-Thoron (2005) suggested, the asymmetric or symmetric learning may have strong impact on the overall efficiency of the equilibrium.

[18] Eling et al. (2015) use a different sample of the same portfolio.

guideline, which standardizes CI insurance products. In this sample, all group policies and insured individuals have the same coverage for the 25 critical diseases. Both group and individual CI insurance are available in the Chinese market. The group CI insurance market is dominated by employee benefits for which the employer pays the premium and the employee contribution is minimal. There are no restrictions regarding risk classification based on age, gender, occupation, region or other possible pricing factors. The insurer has sole discretion to determine the price offered for both new and renewed contracts. The market is commercial and voluntary. Thus, the concerns regarding risk reclassification, availability, and affordability of such insurance are minimal.

The group CI insurance falls into the no commitment category, where the insurer is free to terminate the group contract at the end of any policy period. The group insured is also free to switch or to terminate the group contract at any time. The individual insured is partially committed to the coverage due to his/her job attachment. Eling, Jia, and Yao (2015) focus on the information structure of group CI insurance and show the presence of between-group adverse selection and asymmetric learning.

Sample B is a portfolio of Loaner’s Personal Accident (PA) insurance. The borrower (insured) of a bank buys the coverage from the insurer to cover his/her accidental death and disability during the loan period. The policy beneficiary is the bank and the insurance amount usually equals the outstanding loans plus interests. The bank also serves as the sales agent of the insurer, recommends this product to its borrowers, and receives sales commission as a percentage of the insurance premium from the insurer. The bank can sell the Loaner’s PA exclusively for one insurer, or for multiple insurers. The borrowers can buy the product from the bank or from other channels. However, after consulting with the insurer, almost all borrowers buy the product from the bank channel, because they are afraid that products from other channels may not 100% meet the bank requirement, shopping products from other channels require additional efforts and knowledge, and products from other channels may be more expensive because individual borrowers may not enjoy a group discount as being insured together with all borrows from the bank. Villeneuve (2014) confirms this channel stickiness for a similar product of mortgage life in French market.

The policy period is usually one year but with an implicit guaranteed renewability until the borrowers clear all loans. This implicit guarantee is strong, because the bank, as the beneficiary, would expect the insurer to cover all its loaners as a group and thus do not accept the insurer’s cherry picking, leaving the bank itself at risk. The bank, as the sales agent, has also the market power to enforce the implicit guarantee. In the agent agreement, the insurer has in fact delegated the underwriting authority to the bank to accept all borrowers as a group. Meanwhile, a rating tariff is also delegated to the bank to insure all risks according to the tariff without further underwriting. The parameters in the tariff include age, gender, and occupation accidental categories. Premiums are not updated based on individual insured’s past claim experience (nondiscriminatory, Pauly, 2003). However, the tariff can be updated from time to time based on “community rating.” The individual insureds partially commit to the long-term coverage, because they are required to insure by the bank as long as they have outstanding loans, and they are reluctant to switch insurers (Villeneuve, 2014). The insured can terminate the coverage or significantly reduce the insurance amount at any time by early pay back (part of) his/her loans, which is very common in the Chinese market. The bank is free to terminate the agent agreement with the insurer at any time and to switch to competing insurers, which results in a considerable proportion of insureds also switching at the time of their next renewal.

The Loaner’s PA falls into the scenario of semi-commitment, where the insurer is committed to the long-term coverage by implicit guaranteed renewability and the insured is partially committed to the long-term coverage by his/her outstanding loans with the bank. This market presents little adverse selection, because almost all banks require all borrowers to present a Loaner’s PA for the loans, thus the product has a compulsory feature for borrowers. The product information structure features as no adverse selection with asymmetric learning.

Both samples include all information that the insurer uses to make underwriting and pricing decisions. Claims records are included. Sample A covers all group CI policies issued between January 2008 and June 2013 and all claims settled between January 2008 and August 2012 under the corresponding policies. Sample B covers all Loaner's PA policies issued between January 2008 and December 2011 and all claims under these policies. The two samples are selected following the same procedure. First, only policies with duration between 360 and 366 days, i.e. 1-year duration, are used and thus policy age and number of renewals are aligned with each other.[19] Second, policies, of which the renewal status cannot been identified, are deleted from the sample. Third, the premium rates are truncated at both the 1 and 99 percentiles to avoid the potential bias of extreme values. The final Sample A contains 5,570 group policy-year observations purchased by 3,152 groups, representing more than 1,880,000 individual policies.[20] Sample B contains more than 1,280,000 individual policy-year observations purchased by over 800,000 individual insureds. Missing information is present in both samples, particularly related to missing claims after August 2012.[21]

As shown in Table 4, the key differences between the two products are in the insurer's commitment type and the presence of adverse selection in early policy periods. Other factors are either the same or largely similar such that any differences in pricing and/or risk patterns likely attributable to differences in commitment type and/or adverse selection. As shown in Table 5, both samples are characterized by a low claim frequency, a relatively small insurance amount for most policies, and a mixture of ages, genders, and occupations. The Loaner's PA portfolio contains much more males than females, which reflect the Chinese family tradition, where the man usually manages the household's external financial relationships, e.g., loans. It also reflects that businessmen outnumber businesswomen in China. The area distributions of the two portfolios are significantly different, where the group CI more concentrates in the developed areas, because firms that could afford the employee benefits tend to locate in more developed and affluent areas.

[19] For Sample A, group policies with 1-year duration account for 62% of all policy-years; for Sample B, policies with 1-year duration account for 82% of all policy-years.

[20] The original data of Sample A are at individual policy level. The individual policy entries are then organized into group policies according to the group policy number.

[21] The claims information is electronically recorded in real time but only retrieved and organized by the actuarial team once per year. When obtained the data for Sample A, the claim information for September 2012 to June 2013 were not yet available. In a later analysis, to avoid a potential truncation problem, the claim status of polices expiring after August 2012 are coded as missing values.

Table 4 Qualitative comparison of samples A and B

	Sample A	Sample B	Comparison
Product	Group critical illness	Loaner's personal accident	
Insurer	Anonymous L&H insurer	Anonymous L&H insurer	Same
Market	China	China	Same
Sample period	2008-2013	2008-2011	Similar
Commitment type	No commitment	Semi-commitment	Different
Insurer's commitment	1-year short-term policy	1-year short-term policy with guaranteed renewability	Different
Bank's or group's commitment	Employer is free to cancel or switch insurer	Bank is free to switch insurer	Similar
Individual insured's commitment	Partially attached due to employment	Partially attached due to the loan with the bank	Similar
Adverse selection	Between-group adverse selection, which diminishes after two periods (Eling et al., 2015)	No	Different
Incumbent insurer's learning	Group level experience rating	Bank level experience rating	Similar
Competing insurers' learning	No information sharing system, but may observe the past claim history at group level by group declaration	No information sharing system, but may observe the past claim history at bank level by bank declaration	Similar

Table 5 Quantitative comparison of samples A and B

		Sample A: Group critical illness						*Sample B: Loaner's personal accident*					
Variables	Descriptions	Obs.	Mean	S.D.	p5	Median	p95	Obs.	Mean	S.D.	p5	Median	p95
Premium Rate	Annualized premium rate per insured	5,489	0.0027	0.0020	0.00066	0.0024	0.0066	1,262,082	0.0027	0.00083	0.0013	0.0028	0.0040
Departure Dummy	1 if the policy is dropped in the next period	3,884	0.39	0.49	0	0	1	803,758	0.53	0.50	0	1	1
Policy Age	Count of renewal times	5,570	0.92	1.16	0	1	3	1,285,629	0.31	0.63	0	0	2
Insurance Amount	Insurance amount per insured in CNY	5,570	60,667.4	74,496.0	3,000	50,000	200,000	1,285,244	37,108.0	21,579.3	10,000	30,000	90,000
Group Size	Number of individual insureds in the group	5,570	342.0	1471.0	6	63	1248	N.A.					
Policy Duration	Policy duration in days	5,570	365.0	0.85	363.6	365	366	1,285,629	364.1	1.02	362	364	365
Sex	(Fraction of) women	5,561	0.41	0.21	0.084	0.40	0.80	1,272,506	0.12	0.33	0	0	1
Age	(Group average) age	5,568	35.7	7.21	24.7	35.8	47.1	1,285,547	40.4	9.01	26	40	56
Work[a]	(Group average) occupation accident tendency	5,460	2.00	1.03	1	1.99	4	1,279,303	2.73	1.21	1	3	4
Area[b]	Indicator of relative wealth and insurance market development of the policy issuance location	5,570	2.03	0.86	1	2	3	1,285,629	3.11	0.67	2	3	4
Claim Dummy	1 if any claim(s) under the policy	2,794	0.14	0.35	0	0	1	1,021,970	0.00074	0.027	0	0	0
Claim Frequency	Average number of claims per insured	2,794	0.00094	0.0050	0	0	0.0048	N.A.[c]					
N	Total number of policies	5,570						1,285,629					

Notes:

a. 1 represents the safest occupations, and 6 represents the most dangerous ones. The variable *work* represents the accident tendency of an occupation, e.g., office workers are 1, and coal mine workers are 6. The insurer accepts very few risks with occupation categories above 4.

b. 1 represents the most developed regions in China, and 4 represents the least developed regions. The variable *area* is based on the insurer's branch categories, which consider not only regional wealth level but also regional insurance development level. It is thus a better control variable than pure wealth measurement.

c. The claim frequency is not applicable for Sample B because it is very close to the claim dummy. Almost all insureds have only one accident claim in one policy, if there is any.

5.2 Models

The same models are applied to both samples. Equation (1) tests Hypotheses 1A and 1B with Sample A and B, respectively. The premium rate is measured by the natural logarithm of the average annualized premium rate per person, *lnPremiumRate.* The insurance *Policy Age* is measured by the number of renewals. All policies in both samples are yearly policies, and thus the renewal times fully capture the policy experience with the insurer. $X_{i,t}$ is a vector of time-variant control variables, including policy features (insurance amount per person and, for Sample A, group size) and risk classification factor (age). Risk classification refers to the use of observable characteristics by insurers to compute the premiums. Y_i is a vector of time-invariant control variables, including risk classification factors (gender and occupation category) and location fixed-effects. $Year_t$ controls for the year fixed-effects.

$$Premium\ Rate_{i,t} = \beta_1 + \beta_2 Policy\ Age_{i,t} + \beta_3 X_{i,t} + \beta_4 Y_i + \beta_5 Year_t + \varepsilon_{i,t} \quad (1)$$

Equation (1) is estimated with OLS regressions. Random-effects and firm fixed-effects[22] models are estimated as robustness tests (Zhang and Wang, 2008; Eling et al., 2015), the results of which are consistent with the core models. Chiappori and Salanie (2000) emphasize that the use of simple, linear functional forms on insurance policy-level data should be restricted to homogeneous populations. The samples approximate homogeneity because (1) the business nature is largely the same as employee benefits for Sample A and as mortgage PA for Sample B; (2) the model includes all relevant pricing factors to account for potential heterogeneity among policies; (3) Robust standard errors clustered by insureds further control for heterogeneity. However, the residual plots suggest some remaining heterogeneity in both samples, thus firm fixed-effects models are used to further reduce the heterogeneity in a robustness test, the results of which are consistent with the core models. The variance inflation factors (VIF) of the independent variables range between 1.02 and 1.63 for Sample A and 1.00 and 1.67 for Sample B. All VIFs are below 5, suggesting multicollinearity is not a problem. The Wooldridge test for autocorrelation in panel data suggests minimal autocorrelation problem in both samples with p-value of 0.67 for Sample A and with p-value of 0.15 for Sample B.

Equation (2) tests Hypotheses 2A and 2B with Sample A and B, respectively. Finkelstein et al. (2005) develop this empirical model to investigate the risk-based dynamic selection. The premium rate is used as the indicator for risk type (HL, 2003). H2A predicts that if no commitment, high risks shall depart from the portfolio over time and thus a positive coefficient is expected between the departure dummy and the premium rate (risk); H2B predicts that if semi-commitment, low risks tend to depart from the portfolio over time and thus a negative coefficient is expected between the departure dummy and the premium rate. $X_{i,t}$ is a vector of policy features (insurance amount per person and, for Sample A, group size); $Location_i$ and $Year_t$ represent the location and year fixed-effects, respectively. The risk classifications (i.e. the insured's demographic features) are not included in Equation (2) because the premium rate has fully captured these information. Equation (2) is estimated with OLS regressions. The corresponding robustness tests are available upon requests.

$$Departure\ Dummy_{i,t} = \beta_1 + \beta_2 lnPremiumRate_{i,t} + \beta_3 X_{i,t} + \beta_4 Location_i + \beta_5 Year_t + \varepsilon_{i,t} \quad (2)$$

[22] It is acknowledged that firm fixed-effects are able to better capture the dynamics of one firm over years; however, its costs are also significant as to omit all time-invariant variables. The results of firm fixed-effects models are present in Table 9, Section 5.5.

5.3 Results on inter-temporal pricing strategy

Table 6 presents the results from Equation (1). The actual premiums are regressed against the complete risk classification control variables and claim experience, where applicable. Thus any trend found between the actual premium and the policy age reflects the inter-temporal pricing strategy controlling for the underlying risk changes. The trend observed does not necessarily reflect the actual increase or decrease of the premium rate but a relative premium increase or decrease to the actuarial fair premium, which is the inter-temporal pricing pattern (KP, 1985; PKH, 1995). The Sample A results in Panel A show positive coefficients between the premium rate and the policy age, indicating a pattern of premium lowballing (back-loaded) and supporting H1A. The Sample B results in Panel B show negative coefficients between the premium rate and the policy age, indicating a pattern of premium highballing (front-loaded) and supporting H1B.

The difference between Column 1 and 2 in Panel A is that Column 2 includes an additional independent variable, the last-period group claim frequency, to capture the experience rating at the group level for Sample A. Its coefficient is positive, as expected, meaning last-period high claim frequency associates with a higher premium rate in the current period. The positive correlation between policy age and premium rate remains. This practice is not applicable to Sample B because the loaner's PA insurance is not experience rated at the policy level.

Looking at the subsample results of Sample A, the premium pattern is flat for the first two periods, and then continuously increases with the policy age in the 2nd, 3rd, and subsequent renewals. KP (1985), Nilssen (2000), and de Garidel-Thoron (2005) suggest that the higher profit or price is viable in later periods because the incumbent insurer can learn the insured's risk type in early periods, and thus can over charge low risks with sticky price. Due to the low frequency nature of critical illness insurance, the insurer's learning process may require longer time. The insured groups may have not yet revealed their risk types in claim experience in the first two periods. This is particularly true for small groups as they may simply be lucky for not having any claims. This explanation is consistent with Eling et al.'s (2015) findings, where they use a different subsample of the same portfolio and show that the insurer learning eliminates information asymmetry (adverse selection) after the first two periods. This flat-increase pattern implies that insurer learning is a necessary condition for the insurer adopting a price lowballing strategy, although early research has found no difference between symmetric and asymmetric learning (Cohen, 2012; Kofman and Nini, 2013, Shi and Zhang, 2015). Looking at the subsample results of Sample B, the premium rate continuously decreases with the policy age. The absolute values of coefficients between policy age and premium rate become smaller over time, suggesting that the scale of premium reduction from year to year becomes smaller and smaller.

Table 6 Results on inter-temporal pricing strategy

	Panel A: Group critical illness insurance						*Panel B: Loaner's personal accident insurance*			
	Full sample		New-->1^{st} renewal	1^{st} --> 2^{nd} renewal	2^{nd}-->3^{rd} renewal	The 3rd and subsequent renewals	Full sample	New-->1^{st} renewal	1^{st} --> 2^{nd} renewal	The 2nd and subsequent renewals
Variables	ln(Premium Rate)						ln(Premium Rate)			
Policy Age	0.0192*	0.0690***	-0.0244	0.0200	0.105***	0.0876***	-0.0790***	-0.1000***	-0.00421***	-0.00149[a]
	(0.0103)	(0.0158)	(0.0167)	(0.0210)	(0.0298)	(0.0303)	(0.000528)	(0.000638)	(0.000923)	(0.00301)
ln(Insurance Amount)	-0.132***	-0.138***	-0.131***	-0.146***	-0.138***	-0.0519	-0.0342***	-0.0331***	-0.0586***	-0.0620***
	(0.0107)	(0.0163)	(0.0105)	(0.0152)	(0.0245)	(0.0380)	(0.000443)	(0.000417)	(0.00118)	(0.00228)
ln(Group Size)	-0.0859***	-0.0597***	-0.0898***	-0.0711***	-0.0667***	-0.0172	-0.0145***	-0.0145***	-0.0289***	0.0154***
	(0.00755)	(0.0109)	(0.00706)	(0.00963)	(0.0155)	(0.0211)	(0.00117)	(0.00111)	(0.00211)	(0.00327)
Sex	-0.207***	-0.00203	-0.274***	-0.000411	0.169	0.216	-0.000486***	-0.000338***	-0.00114***	-0.00123***
	(0.0455)	(0.0745)	(0.0442)	(0.0716)	(0.125)	(0.167)	(3.88e-05)	(3.63e-05)	(7.80e-05)	(0.000120)
Age	0.0430***	0.0404***	0.0446***	0.0438***	0.0393***	0.0507***	-0.106***	-0.0948***	-0.299***	-0.343***
	(0.00174)	(0.00262)	(0.00165)	(0.00230)	(0.00337)	(0.00428)	(0.000793)	(0.000752)	(0.00186)	(0.00388)
Work2	-0.0676**	-0.0946**	-0.000971	-0.0715*	-0.265***	-0.347***	-0.119***	-0.115***	-0.158***	-0.157***
	(0.0297)	(0.0464)	(0.0294)	(0.0383)	(0.0610)	(0.0762)	(0.00154)	(0.00146)	(0.00299)	(0.00488)
Work3	-0.212***	-0.147***	-0.210***	-0.179***	-0.242***	-0.380***	-0.0636***	-0.0753***	-0.148***	-0.143***
	(0.0278)	(0.0432)	(0.0270)	(0.0369)	(0.0608)	(0.0881)	(0.000975)	(0.000925)	(0.00219)	(0.00437)
Work4	-0.0493	-0.00367	-0.0683	-0.0357	-0.0154	-0.128				
	(0.0432)	(0.0482)	(0.0473)	(0.0501)	(0.0664)	(0.104)				
Work5	0.0766	0.182**	-0.00149	0.206	0.0267	0.0119				
	(0.0682)	(0.0852)	(0.0768)	(0.132)	(0.190)	(0.158)				
Prior Claim Frequency		3.697**								
		(1.729)								
Location/Year FE /Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.368	0.354	0.399	0.377	0.322	0.393	0.161	0.114	0.391	0.514
Observations	5,369	2,269	4,109	2,250	1,020	603	1,242,577	1,151,290	278,893	91,287

Notes:

The table reports the estimated coefficients of OLS regressions. Robust standard errors clustered by insureds are presented in parentheses. It also presents *, **, ***, indicating significant differences of coefficients from 0 at the 10%, 5%, and 1% levels, respectively.

a. The coefficient becomes less significant in this subsample probably due to the small number of observations.

Looking at the control variables, the actual premium rates negatively associate with the insurance amount (group size), suggesting the discount for large quantity of insurance (large clients). Women enjoy a lower rate than men because women are less likely to have critical illness and less likely to have accidents than men. Older people have a much higher critical illness risk and a slightly lower accident risk than younger people. The occupation types, by definition, reflect the propensity for accidents, instead of illness. Thus, as expected, people in the safer categories have a lower premium rate of accident insurance.

Products A and B yield the opposite inter-temporal pricing patterns, which cannot attribute to the idiosyncrasies of insurers, markets, or time periods by the two-sample constructs, but to the product differences in the insurer's commitment type and/or in adverse selection as highlighted in Table 4. The comparison results based on synthesized empirical evidence have successfully excluded adverse selection as a determinant of the inter-temporal pricing strategy. Moreover, the adverse selection becomes minimal in Sample A after the first two contract periods (Eling et al., 2015), and thus both samples have no adverse selection when the pricing patterns are significant. Thus the opposite inter-temporal pricing patterns can reasonably attribute to the different types of the insurer's commitment. This unique empirical design strengthens the correlation between the insurer's no commitment and its lowballing pricing strategy and between the insurer's pre-commitment and its highballing pricing strategy, by controlling for the differences in insurers, markets, and sample periods.

5.4 Results and Discussion on risk-based dynamic selection

Tables 7 presents the results from Equation (2). The Sample A (B) results in Panel A (B) show negative (positive) coefficients between the risk (measured by premium rate) and the departure dummy, indicating low (high) risks depart and high (low) risks stay in the portfolio over time, which is against H2A (H2B). The subsample results in Columns 2 and 3 confirm the same trend as the full sample in Column 1.

The question is then why? Do the observed risk dynamics result from the risk-based dynamic selection or from other factors? The demand driving factors other than the risk may provide a promising explanation. In Sample A, the insured group can cancel the policy because of bad economic environment or changes in management, which have nothing to do with whether the group is high- or low-risk. In Sample B, the insured may decide to pay back the loans because of a decrease in market interest rate, which enables him/her to access to less expensive financial resources. Moreover, the expected insurance benefits are very small in both samples. It is unlikely that the insureds would change their job or loan plan considering such small benefits. Therefore, the risk dynamics observed are very likely not risk-based but driven by other insurance demand factors. To verify this explanation, GDP growth rate for Sample A and 1-year loan interest rate for Sample B are alternatively included in the models, to replace the risk measurement (premium rate). The year fixed effects are omitted due to their multicollinearity with the macroeconomic indicators. The results in Column 4, Table 7 show that, as expected, a low GDP growth associates with high policy cancellation rate with respect to CI employee benefits; a low (current) interest rate indicates a low finance cost for the current period, thus the insured (borrower) is easier to pay back prior loans and cancel the PA policy.[23]

[23] There might be an opposite incentive as that the low interest rate environment keeps the loaner paying back the loans slowly due to reduced interest cost, while high interest rate environment speeds up the pay-back due to increased interest cost. However, the empirical evidence does not support this argument. A high interest rate usually indicates a liquidity shortage in the market and thus is a more difficult situation to pay back the loans.

Table 7 Results on risk dynamics

	Full Sample	New Policies	Renewed Policies	Full Sample
Variables	Departure Dummy			
Panel A: Group critical illness insurance				
ln(Premium Rate)	-0.0710***	-0.122***	-0.0155[a]	
	(0.0167)	(0.0227)	(0.0171)	
Real GDP Growth				-0.0135**
				(0.00622)
ln(Insurance Amount)	-0.0615***	-0.0857***	-0.0256**	-0.0500***
	(0.0106)	(0.0150)	(0.0118)	(0.00951)
ln(Group Size)	-0.0837***	-0.0976***	-0.0425***	-0.0757***
	(0.00684)	(0.0108)	(0.00764)	(0.00656)
Location FE/Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
R^2	0.063	0.081	0.041	0.055
Observations	3,834	1,718	1,726	3,884
Panel B: Loaner's personal accident insurance				
ln(Premium Rate)	0.350***	0.412***	0.0986***	
	(0.00281)	(0.00307)	(0.00535)	
Interest Rate				-0.0511***
				(0.00147)
ln(Insurance Amount)	-0.0307***	-0.0226***	-0.0344***	-0.0554***
	(0.000986)	(0.00119)	(0.00204)	(0.000922)
Location FE/Constant	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
R^2	0.304	0.306	0.258	0.016
Observations	784,494	588,155	180,696	803,373

Notes:
The table reports the marginal effects after logistic regressions at the means of the independent variables. Robust standard errors clustered by insureds are presented in parentheses. It also presents *, **, ***, indicating significant differences of coefficients from 0 at the 10%, 5%, and 1% levels, respectively. a. p value equals to 0.36.

The roles of commitment and information in inter-temporal risk-based dynamic selection is more complex and less conclusive than their roles in the product pricing strategy. First, the dynamics of high and low risks in a portfolio is a two-side decision: the insurer can "select" risks by re-underwriting, experience rating, menu contracts, and by an inter-temporal product pricing strategy; the insureds also decide whether they stay or depart considering competing offers, own risk types, and other insurance demand factors. It may be easy to argue that both highballing and lowballing pricing strategies (strategy of the supply side) generate lock-in effects for low risks (Nilsson, 2000; HL, 2003; Hofmann and Browne, 2013); however, the results of such lock-in effects, combining with the force from the demand side, remain an undetermined empirical question. It is still subject to the empirical examination whether high or low risks depart in a particular product portfolio.

Second, both commitment and information conditions play a role in risk-based dynamic selection. Under the no commitment scenario, re-underwriting is one of the tools to do risk-based selection, which by its nature requires the insurer update the risk type related information. Such insurer learning can either be symmetric or asymmetric, but no learning would result in no supply-side selection over multi-periods. Under the semi-commitment scenario, CH (1987) suggest that high risks depart from the long-term coverage, because the insurer can offer menu contracts of both short-term and long-term, where high risks choose the short-term and low risks choose the long-term. However, such a separating equilibrium depends on the presence of adverse selection and asymmetric learning. HL (2003) suggest low risks tend to depart from the long-term coverage, because competing insurers would apply a cream-off strategy and target at the low risks. Such an argument depends on the symmetric learning condition, which allows competing insurers also to distinguish low risks from high risks. Therefore, it is reasonable to conclude that the insurer learning is a necessary condition for any risk-based dynamic selection.

Empirical research, however, is limited on risk-based dynamic selection. Under the no commitment scenario, Cohen (2012), Kofman and Nini (2013), and Shi and Zhang (2015) show that the high-risk departure pattern in short-term contracts does not depend on the type of learning. Under the semi-commitment scenario, Finkelstein et al. (2005) and Pinquet et al. (2011) support HL's (2003) prediction that the low risks tend to depart even with the highballing pricing strategy in place to lock them in. However, Dionne and Doherty (1994) show the opposite in a market with adverse selection, a menu contract could sort low risks into long-term contracts.

The contribution of this paper in respect of risk-based dynamic selection lies with the following implications. First, the observed risk type-departure pattern, even if it is significant and economically strong, it might not be the result of risk-based dynamic selection. The illusory patterns found in the two-sample empirical design are driven by the decisions of employee benefits and of early loan clearance, rather than the risk types. Second, in order to identify the risk-based selection effects, one must control for risk dynamic drivers from both supply and demand sides and thus isolate the product differences in both commitment and information structures. Third, the paper concludes that the insurer learning is a necessary condition for any risk-based dynamic selection, based on the synthesis review.

5.5 Robustness Tests

First, as the pricing pattern should result in a corresponding profit pattern, D'Arcy and Doherty (1990) compare loss ratios of different policy age cohorts to identify the inter-temporal pricing strategy. This approach is less favorable to the regression with Equation (1) because (1) it does not control for the underlying risk differences, thus the profit pattern observed may result from the risk changes instead of the pricing strategy; (2) for low frequency products, as with the two samples in this paper, the volatility of actual loss ratios are significant;[24] and (3) the "incurred but not reported (IBNR)" claims become significant for policies issued in later years, which further bias the loss ratio measurement. As a robustness test, Table 8 presents the loss ratio patterns over the policy age cohorts. The results for Sample A confirm the lowballing pricing pattern found in the premium rate regressions with Equation (1). However, for Sample B, it is hard to say there exists any loss ratio pattern, because there happens to be very few or no claim in policy cohorts older than 2 years, indicating a strong IBNR bias in this portfolio. Therefore, as mentioned above, the regression approach to directly identify the pricing, instead of the profit, pattern seems a better choice.

Table 8 Loss ratios by policy age cohorts

	Sample A		Sample B	
Policy Age	Loss Ratio	Observations	Loss Ratio	Observations
New	38.5%	2,516	23.2%	955,752
1st renewal	30.8%	1,593	12.5%	195,538
2nd renewal	24.6%	657	4.0%	83,355
3rd renewal	17.7%	363	0	5,327
4th renewal	3.8%	168	0	2,605
5th renewal	1.2%	72	N.A.	N.A.
Total	31.5%	5,369	20.0%	1,242,577

[24] Low frequency is not a problem to detect adverse selection and reflect the insurer learning as discussed in Eling et al. (2015), however which indeed increases the randomness of the loss ratio measurement.

Second, Equation (1) is estimated with random-effects and firm fixed-effects approach.[25] The results shown in Table 9 support H1A and H2B. The advantage of firm fixed-effects is that the coefficients mostly capture the dynamics of one firm over years, i.e. the time series effects, instead of the cross-sectional effects. Thus it best identifies the pricing pattern for one firm over time. However, firm fixed-effects models have to omit all time-invariant or less variant variables, such as gender, occupation, age, insurance amount, and group size, which are important pricing factors should be controlled. Moreover, fixed-effects models may significantly reduce the estimation efficiency in a short panel as with the two samples of this paper. Random-effects models are more efficient than fixed-effects. The samples of this paper largely meet the assumptions of random-effects model: (1) the insureds can be considered as a random sample of the nationwide population, and (2) the uncontrollable firm heterogeneity is random and not correlated with the error terms (Greene, 2011; Gujarati, 2010).[26] The use of panel regression approach as robustness tests instead of core models is also because one firm can buy two or more policies in nth year. All of these policies have the policy age of n, however, only one of them can be incorporated in the panel regressions. Thus, 14.8% of Sample A and 7.9% of Sample B have to be dropped from the respective samples if using the penal regression approaches, which further reduces the estimation efficiency.

[25] The implications on risk-based dynamic selection (see Section 5.4) do not depend on the model specifications. Thus, the robustness tests with Equation (2) are not present here but available upon requests.

[26] Zhang and Wang (2008) discuss why and how to apply random-effects models in a dynamic insurance market.

Table 9 Random- and fixed-effects models

Sample	Sample A			Sample B	
Model	RE		FE	RE	FE
Variables	ln(Premium Rate)				
Policy Age	0.00704	0.0306***	0.0194*	-0.00297***	-0.00190***
	(0.00673)	(0.0104)	(0.0116)	(0.000136)	(0.000148)
Prior Claim Experience [a]		0.468			
		(0.831)			
ln(Insurance Amount)	-0.142***	-0.153***		-0.0258***	
	(0.00869)	(0.0140)		(0.000424)	
ln(Group Size)	-0.0801***	-0.0432***			
	(0.00557)	(0.00824)			
Sex	-0.184***	-0.0329		-0.0135***	
	(0.0407)	(0.0687)		(0.000952)	
Age	0.0376***	0.0354***		-2.55e-05	
	(0.00135)	(0.00202)		(3.40e-05)	
Work1				-0.122***	
				(0.000729)	
Work2	-0.00922	-0.0367		-0.160***	
	(0.0182)	(0.0256)		(0.00115)	
Work3	-0.100***	-0.0678**		-0.108***	
	(0.0179)	(0.0269)		(0.000790)	
Work4	-0.00434	0.0494			
	(0.0325)	(0.0433)			
Work5	-0.0103	0.0350			
	(0.0643)	(0.0772)			
Location FE	Yes	Yes	No	Yes	No
Year FE /Constant	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.354	0.334	0.042	0.138	0.205
Observations [b]	4,803	1,999	4,916	1,149,541	1,164,759

Notes:

The table reports the estimated coefficients of random- and fixed-effects regressions. Standard errors are presented in parentheses. It also presents *, **, ***, indicating significant differences of coefficients from 0 at the 10%, 5%, and 1% levels, respectively.

a. Claim experience is only applicable to Sample A and to random-effects models because Sample B does not allow for experience rating and fixed-effects cannot incorporate time-invariant variables (prior claim experience is 0 for most observations due to the low frequency nature of this portfolio).

b. The smaller number of observations results from that one firm buys two or more policies in nth year. All of these policies have the policy age of n, however, only one of them can be incorporated in the panel regressions. Policies signed earliest in the year are used and others are dropped. This process does not affect the conclusions.

6. Concluding Remarks

This paper concludes the roles of commitment and information structure in determining the insurer's inter-temporal pricing strategy. The results from both synthesized and new evidence confirm that the lack of insurer's pre-commitment to multi-period insurance relationship predicts the price lowballing strategy (H1A) and its pre-commitment predicts the price highballing strategy (H1B). In addition, the insurer learning, either symmetric or asymmetric, is a necessary condition for the price lowballing strategy, because lowballing requires the incumbent insurer to discriminate low risks from high risks based on new information learned with policy experience. The insurer learning and the learning type are not the necessary condition for the price highballing strategy, because highballing can be implemented with a level premium or a pre-agreed premium schedule, which do not necessarily involve a price update over multi-periods. The pricing strategy is sensitive neither to the presence of adverse selection nor to the type of insured's commitment.

This paper also discusses the determinants of risk-based dynamic selection (Finkelstein et al., 2005). The new empirical evidence shows that any risk dynamic pattern observed could be a combined result of both supply (the insurer's selection) and demand (the insured's self-selection) decisions, and thus explains the discrepancy in extant evidence (see Table 3). The implications are also that both commitment and informational assumptions play a role in risk-based dynamic selection and the insurer learning is a necessary condition for any risk-based dynamic selection.

The conclusions on pricing strategy and risk dynamics may also be useful in other industries, which have similar multi-period contracting market and switching possibilities over time. One of such examples is the commercial banking industry, where loan applicants rejected by one bank can apply at other banks (Shaffer, 1998). This feature yields a pattern that incumbent banks keep low-risk loaners and competitors innocently attract those high-risk ones. The highballing pricing strategy has been proved to be useful to lock-in low-risk consumers, which is implemented in the insurance industry in the form of a pre-agreed premium schedule. This design may be applicable to the banking industry, where a bank charges a relatively high loan rate or a fixed amount of fees in early periods, and charges relatively low rate and no fees in later periods. The highballing pricing strategy also insures the reclassification risk, where the bank (insurer) charge additional fees (premium) to ensure the customers no or low rate increase in the future even if the customer's credit (insurance) risk increases.

Future theoretical work may unite the different forces driving risk dynamics in one model. Future empirical work should carefully control various sources of selection and self-selection, thus to isolate the impact of risk type and pricing strategy on risk dynamics. Ideally, the optimal dataset to test risk-based dynamic selection should be those of private term life insurance as used by Hendel and Lizzeri (2003), where the decision of purchasing insurance is more driven by the risk consideration rather than other insurance demand factors. In addition, different durations of term life insurance (e.g. yearly renewed vs. 10-year term life) naturally construct the comparison between no commitment and semi-commitment scenarios. Moreover, the meta-analysis (Kysucky and Norden, 2014) may contribute to compare the magnitude of pricing strategies, as for some products, the highballing or lowballing pricing pattern maybe more significant than other products. Such demand of meta-analysis also calls for more empirical samples in the field of multi-period insurance contracting. As compared to the single-period information asymmetry literature, the multi-period insurance contracting research remains at an evolutionary stage.

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