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The Effects of Macroprudential Policy on Hong Kong's Housing Market: A Multivariate Ordered Probit Augmented Vector Autoregressive Approach

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Abstract

This study evaluates the effects of macroprudential policy on Hong Kong's housing market using a multivariate ordered probit-augmented vector autoregressive model (MOP-VAR). The proposed MOP-VAR extends the conventional dummy policy variable approach by allowing explicit measurement of time-varying policy intensities that underlie policy rules, and thus facilitates analyses of bilateral relationship between house prices and multiple policy instruments when endogeneity exits among the instruments' intensities and prices. An impulse response analysis suggests that the dampening effect of macroprudential tightening is stronger and more instantaneous on transactions than on prices. The eventual outcome as indicated by conditional forecasts is dominated by a strong and prolonged own price response to house price shocks and other external developments that undermine the policy's effectiveness. Moreover, over the long haul, a combination of a stamp duty and stress test tends to be more effective than restricting the loan-to-value ratio in triggering a trend reversal in house prices, despite the government's preference for the latter. The out-of-sample probabilistic forecasts of policy changes are mostly consistent with the observable outcomes.

Keywords: Housing market; macroprudential policy; Hong Kong; Bayesian; vector autoregression; multivariate ordered probit.

JEL classifications: R38; E58; C11; C31.

1. Introduction

Hong Kong has the world's most unaffordable housing.[1] Since the 1997 Asian Financial Crisis, the Hong Kong Special Administrative Region (HKSAR) Government has frequently adjusted the intensities of several macroprudential policy instruments aiming to stabilize the housing market. As property prices rallied on the back of a zero-bound interest rate and quantitative easing (QE), the extent of government intervention intensified. However, the effectiveness of macroprudential policy is a subject of debate in Hong Kong as house prices kept surging after successive rounds of policy tightening. A survey conducted by the Chinese University of Hong Kong reveals no significant changes in the number of respondents planning to buy houses before and after the Government's announcement of macroprudential policies (Ho *et al*., 2010).

Among various macroprudential policy instruments, the Hong Kong Monetary Authority (HKMA), the *de facto* central bank of Hong Kong, strongly favors the loan-to-value (LTV)

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[1] 14th Annual Demographia International Housing Affordability Survey 2018. Available at: http://www.demographia.com/.

policy and has persistently bragged about its usefulness (HKMA, 2011). Systematic assessments of its effects are available but far from abundant. For instance, Gerlach and Peng (2005) study the link between house prices and the financial sector in Hong Kong and discuss the scope for macroprudential manipulation. Analysis of factors other than LTV policy is virtually non-existent.

In most empirical studies, macroprudential policy is proxied by a binary variable that marks the periods when a policy is in place (e.g., Cerutti *et al*., 2015; Tillmann, 2015; Akinci and Olmstead-Rumsey, 2017). Such a dichotomous indicator, which signifies the presence and duration of a policy without giving any information about its intensity, is insufficient for evaluating the macroprudential policies in Hong Kong where policy spectrum is multidimensional and policy intensities are time-varying. For instance, the cap on the LTV ratio is a step function over time given the infrequent changes. Likewise, other policy options come with time-varying terms and conditions (e.g., the stamp duty levied on different house price ranges or contingencies is variable) that can only be numerically represented by categorical variables. The degree of policy intensity also differs across instruments both contemporarily and temporally, which may indicate a certain degree of policy correlation or substitutability.

This study evaluates the effectiveness of macroprudential policy in Hong Kong using a new empirical tool, i.e., the multivariate ordered probit-augmented vector autoregressive model (MOP-VAR). The subject choice is premised on the fact that Hong Kong is one of those rare geographical areas where housing prices are publicly available and are reliable. MOP-VAR is essentially a vector autoregression supplemented with a dynamic multivariate ordered probit model. A prominent feature of MOP-VAR is the explicit modeling of changing policy intensity, which is largely absent from current approaches. Our approach reveals richer dynamics in the transmission mechanism and offers a more complete representation of the scope of policy manipulation. The model provides a comprehensive analysis of the endogeneity and bilateral relationship between house prices and various macroprudential policy instruments. Specifically, the MOP-VAR allows probabilistic assessment of (i.e., the timing of) policy changes that are of interest to home buyers and sellers.

Findings from our MOP-VAR impulse response analysis suggests that major macroprudential policy instruments have varying negative effects on house prices in Hong Kong. A conditional forecast analysis further suggests that lifting some of these policy instruments may elevate the house price trajectory. The MOP-VAR out-of-sample probabilistic forecasts of the timings of policy changes are mostly consistent with the observable outcomes. Over the long haul, a combination of a stamp duty and stress test tends to be more effective than the loan-to-value ratio in triggering a trend reversal in house prices, despite the government's preference for the latter. The results of the model diagnostics favor MOP-VAR over several benchmark models.

The rest of this paper is organized as follows. Section 2 gives an account of Hong Kong's experience in macroprudential management. Section 3 explains the technical details of MOP-VAR. Section 4 describes the data. Section 5 evaluates the policy effectiveness based on MOP-VAR and checks our model's ability in making out-of-sample forecasts of policy changes. Section 6 presents our conclusions.

2. Macroprudential Policy in Hong Kong

Macroprudential policy was first proposed in the late 1970s (Clement, 2010). The relative lack of interest during the pre-crisis era, except among regulatory authorities (e.g. Crockett, 2000). Marrying the micro- and macro-prudential dimensions of financial stability), was mainly caused by poorly defined policy objectives and inadequate academic coverage. Incessant efforts by theorists (e.g., Mendicino and Punzi, 2014; Farhi and Werning, 2016) and empiricists (e.g., Lim *et al*., 2011) in the past decade have enhanced our understanding of the subject. Macroprudential policy primarily targets the housing market (Galati *et al.*, 2011; Akinci and Olmstead-Rumsey, 2017) with countering externalities in the credit creation process (Bianchi, 2010; Angelini *et al.*, 2013) being its major underpinning. Further information about the topic can be found in, for instance, the comprehensive review of Galati and Moessner (2013).

This study assesses the effectiveness of macroprudential policy in Hong Kong, where houses are most unaffordable in the world. For the sake of lucidity, Table 1 tabulates episodes of Hong Kong's macroprudential policy tightening in chronological order. The loan-to-value (LTV) ratio has been the benchmark macroprudential policy tool in Hong Kong since the 1990s (HKMA, 2011), although the spectrum of tools has expanded in recent years to include items such as an *ad hoc* buyer stamp duty and a stress test requirement. Apart from the brief tightening ahead of the market peak in 1997, the HKSAR government capped the LTV ratio at the normalized level of 70% for long periods before engaging in multiple rounds of tightening after the subprime crisis.

*** Insert Table 1 here ***

Unlike monetary policy, where the guidelines and criteria (e.g., the Taylor rule) for action are often clear-cut, the catalysts for macroprudential policy changes in Hong Kong are less well defined. The HKSAR government has stated that they refer to a host of different market indicators. High on the list are affordability and the extent of speculative activities.[2]

Based on Table 1, key elements in each of the seven successive rounds of policy tightening since 2009 are highlighted as follows.

1st Round: The maximum LTV was tightened from 70% to 60% for properties valued at or above HK$20 million.

2nd Round: The values of properties subject to the 60% maximum LTV were tightened to HK$12 million or above. The maximum LTV ratio was tightened to 60% for all properties not intended to be occupied by the owners. In addition, banks should stress test mortgage applicants' repayment ability, assuming an increase in mortgage rates of at least two percentage points, and limit the stressed debt-service ratio (DSR) to a cap of 60%.

3rd Round: The maximum LTV was further tightened to 50% for properties valued at or above HK$12 million. The maximum LTV for all non-owner occupied properties was further tightened to 50%. In addition, buyers were required to pay a 15% special stamp duty (SSD) if the time between acquisition and disposal was shorter than 6 months.

4th Round: The values of properties subject to the 50% maximum LTV were tightened to HK$10 million or above. The stressed DSR cap was tightened from 60% to 50%.

[2] The gap with respect to historical market peaks could also be a subtle reference. These indicators are repeatedly mentioned in official quarterly economic reports in defense of interventions.

5th Round: An additional LTV constraint required that if a mortgage applicant already had outstanding mortgages for one or more properties at the time of application, the maximum LTV could not exceed 30%. The SSD increased from 15% to 20% if the time between acquisition and disposal was shorter than 6 months. In addition, a 15% buyer stamp duty (BSD) was imposed.

6th Round: The maximum LTV was further cut by 10% for non-owner occupied and non-residential properties. In addition to the SSD and BSD, a double stamp duty (maximum 8.5%) was imposed. Stress tests were based on an increase in mortgage rates by at least three (previously two) percentage points.

7th Round: The maximum LTV was tightened to 60% for owner-occupied properties valued at HK$7 million or below (previously 70% for properties below HK$8 million).

The time-varying policy intensity as well as the multi-dimensional nature of macroprudential policy as implied in Table 1 render the conventional dummy variable approach insufficient for policy assessment. The next section proposes our MOP-VAR that not only endogenizes the intensities of multiple policy instruments, but also allows such intensities to vary over time.

3. Methodology

3.1 MOP-VAR Specification

Unlike studies that either captured the implementation of each policy instrument using a dummy variable (e.g., Cerutti *et al*., 2015; Tillmann, 2015; Akinci and Olmstead-Rumsey, 2017) or ignored the possible endogeneity among the intensities and propensities of different policy instruments (e.g., Lim *et al*., 2011), our MOP-VAR approach endogenizes the intensities of multiple policy instruments and allows such intensities to vary over time. In essence, MOP-VAR is an augmentation of Dueker's Qual-VAR (2005), in which the binary policy indicator is replaced with a multivariate ordered probit (MOP) structure. It is similar to the conventional Qual-VAR in that the *propensity* of policy implementation is latent and, together with other endogenous variables, follows a vector autoregressive (VAR) process. The difference lies in the specification of the latent variables. Instead of a single binary variable, the unobserved propensities map back to a vector of categorical variables in which the identified categories or levels represent different degrees of observed policy intensity. Our specification bears resemblance to the multivariate dynamic probit model of Candelon *et al.* (2013) except that they stipulate a vector of binary probit variables rather than an ordered structure. We define a MOP-VAR process as follows:

$$\tilde{Y}_t = \begin{bmatrix} Z_t \\ Y_t^* \end{bmatrix} = \sum_{j=1}^{p} A_j \begin{bmatrix} Z_{t-j} \\ Y_{t-j}^* \end{bmatrix} + BW_t + u_t, \qquad u_t \sim N(0, \Sigma), \tag{1}$$

$$Y_t^* = \begin{bmatrix} y_{1t}^* \\ \vdots \\ y_{qt}^* \end{bmatrix} = \left(I_q \otimes X_t'\right)\beta + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Omega), \quad \text{and} \tag{2}$$

$$y_{it} = \begin{cases} 0 & \text{if} \quad -\infty < y_{it}^* \le c_{i1} \\ 1 & \text{if} \quad c_{i1} < y_{it}^* \le c_{i2} \\ & \vdots \\ K_i & \text{if} \quad c_{iK_i} < y_{it}^* \le +\infty \end{cases}, \qquad i = 1, \cdots, q, \tag{3}$$

where Z_t is a set of m observed endogenous variables and Y_t^* is a q-dimensional vector of latent variables representing the propensities of adopting each of the q macroprudential policy instruments. W_t is a set of n exogenous variables including the intercept. A_j and B are conforming coefficient matrices and u_t is a normally distributed error vector.

The latent vector Y_t^* is governed by the multivariate ordered probit process of (2) and (3), where X_t is a set of r reference variables being monitored for deploying policies. The error vector ε_t is normally distributed with non-zero correlations. $\{y_{it}\}$ is the observable counterpart of Y_t^*, and the realized categories (policy intensities in our context) are jointly defined by the thresholds $\{c_{ik}\}$, the state of the reference variables X_t, and the coefficient vector $\beta = [\beta_1', \cdots, \beta_q']'$. Note that the magnitude of policy intensity $K_i + 1$ can differ across the q policy instruments. Finally, equations (2) and (3) imply that the thresholds of changing propensity, $\{c_{ik}\}$, are subtly related to the policy rules summarized in X_t, rather than being a set of independently unidentified model parameters.

3.2 Estimation Procedures

The system comprising equations (1) - (3) can be solved using the Bayesian Markov chain Monte Carlo (MCMC) approach. We highlight the major features and steps here and give details in the Appendix. First, the VAR order p is chosen based on the Bayesian Information Criterion (BIC). A standard Minnesota prior (Doan *et al.*, 1984) is imposed on the parameters of the VAR in (1). This assumes, *a priori*, that the VAR is a random walk and it pins down elements of the prior covariance matrix of the VAR coefficients with designated tightness. The prior distributions for the parameters of the ordered probit (2) and (3) follow those used in Albert and Chib (1993). We propose a normal prior for the

MOP coefficients and diffuse priors for the thresholds. Given these formulations, the conditionals of the VAR parameters are normal and the inverted-wishart and sampling via Gibbs steps are straightforward. A similar argument applies to the coefficients of the regression equation (2), as the conditional is also conjugate. We restrict the diagonals of Ω to 1 for identification purposes, and the correlation term ρ can be obtained easily from the residuals $\hat{\varepsilon}_t$. For consistency, we normalize the simulated β using the respective variances of the unrestricted estimate of Ω.

The sampling of the thresholds c_{ik} and the latent variables Y_t^* warrant special attention. The conditionals of the thresholds are uniform distributions with supports defined by the realized latent variables and the sampling can be done in a Gibbs step. Unlike standard probit models, however, the latent variables cannot be drawn from simple truncated normals because of their temporal correlations with other model elements in (1). Instead, this updating step is performed using a constrained Kalman filter and smoother embedded in a forward-filtering backward-smoothing algorithm. The entire simulation process is initiated with the predicted values of the univariate ordered probit models estimated separately using the policy observables y_{it}.

3.3 Method of Impulse Response Analysis

Like other VAR variants, the core of the MOP-VAR analysis lies in the identification of the structural shocks and the responses of the system to their propagation. This is important from a policy perspective, as behavioral restrictions are lacking in the specification in (1) and the economic interpretation of the reduced form parameters is inconsequential. Without prior knowledge (or assumptions) of how the endogenous variables theoretically interact and how they are causally ordered, we compute the Generalized Impulse Response Functions (GIRF) developed by Koop *et al.* (1996) that produce system responses invariant to variable orderings. Specifically,

$$GIRF_h^i = E\left(\tilde{Y}_{t+h} \mid \epsilon_{i0}, \mathcal{H}_t\right) - E\left(\tilde{Y}_{t+h} \mid \mathcal{H}_t\right), \quad h = 0, 1, 2, \cdots \quad , \quad (4)$$

where $E(\cdot \mid \cdot)$ denotes the conditional expectation, $\mathcal{H}_t$ is the history up to time t, h is the forecast horizon, and ϵ_{i0} is the prescribed shock to the i^{th} variable at time 0. First, the VAR process can be simulated a number of times, and in each iteration a dual copy of the random errors is generated. The designated shock ϵ_{i0} is then imposed onto the duplicate at impact time 0. Propagate the VAR with both sets of errors, and the sample mean or median of the differences give the GIRF of interest.

3.4 Method of Forecasting

Policy evaluation is not complete without the assessment of counterfactuals. In VAR studies, this is commonly dealt with by conditional forecasting. MOP-VAR explores the trajectories of the forecast variables subject to different scenarios that are assumed to have taken place in the past. The intricacy of the task lies in regenerating model parameters that are consistent with these presumptions. We opt for Bańbura *et al*'s. (2015) Kalman filter recursion for conditional forecasting. The required prediction steps of the Kalman filter are quite standard, but the updating steps are executed with matrices of reduced dimension that contain only the future values of the conditioned variables. In essence, the conditional forecasts, or the counterfactuals of the unrestricted variables, are treated as missing values in the recursion and have no role to play in the Kalman updating. The forecasts of interest are then obtained using the computationally efficient Durbin and Koopman (2002) smoother.

In addition to performing conditional forecasting, we assess the ability of the MOP-VAR to capture possible turns in macroprudential policy propensities using out-of-sample forecasting. As in Dueker (2005), this latter exercise is not executed via recursive estimation and an update, but rather focuses on a period with visible regime changes. This is reasonable, as the aim is to predict the probability of the occurrence of specific events; thus, the forecasting accuracy of latent variables — the policy propensities in our context — is relatively nonessential due to the variables' unobservability. The probability forecasts can be computed by counting the simulation iterations that satisfy certain prescribed conditions in relation to the defined events.

4. Data

All the data for this study are available from official sources open to the public and the variables are intuitively selected. Endogenous growth models proposed by Rebelo (1991), Leung (2001, 2003), and Cheng *et al*. (2010) embody an endogenous relationship between the stock of houses, house prices, and non-housing goods. Similarly, most housing studies model house prices as a function of household incomes, mortgage rates, and housing starts (e.g., see Drake, 1993; Ashworth and Parker, 1997). Moreover, in the theoretical model of Ortalo-Magne and Rady's (2006) housing market dynamics under credit constraints exhibits a correlation between house prices and transactions (see also Krainer, 2001). Therefore, natural candidates of the $m = 5$ dimensional vector of the endogenous variable

Z_t include real property price, total transactions, new building completion, real mortgage interest rate, and real non-housing-related aggregate output. The price index covers all of the residential property classes (differentiated by floor size and available from the Rating and Valuation Department) and is deflated by the composite consumer price index (available from the Census and Statistics Department). The transactions include all of the primary and secondary market deals recorded by the Land Registry. Completions are measured in usable floor area terms and are obtained from the Buildings Department. Strictly speaking, the mortgage interest rate (available from the HKMA) is not entirely endogenous, as it basically moves in tandem with the U.S. rates under the pegged exchange rate system. Its inclusion is due to two considerations. First, competition between banks for mortgage business means that the trend in interest rates is not totally independent of property market development. Second, treating the mortgage rate as endogenous facilitates the analysis of the role of QE in stimulating the recent market rally. Non-housing-related economic output is measured by real GDP minus buildings and construction-related capital formation (both from the National Income Accounts) and is introduced to account for non-property-related economic performance.

We consider a bivariate latent vector Y_t^* (i.e., $q = 2$), the elements of which represent the propensities of using (i) LTV policy and (ii) stamp duty and stress test measures (SDST), respectively.[3] Based on the stages of policy implementation shown in Table 1, the LTV policy intensity indicator escalates from level 0 to 7 indicating the tightening of LTV in

[3] The dimension can, in theory, be extended to cover other options such as debt servicing ratio restrictions or to measure the stress test requirement separately. However, we face a potential problem of identification, as some policies are highly synchronized in our case. As a result, the second latent propensity is designed to capture the joint adoption of a stamp duty-related policy and/or a stress test requirement, which are the two most influential policy options other than the LTV ratio.

rounds 1-7 while the SDST indicator surges from level 0 to 6 as the stamp duty and stress test requirements stiffened over the same period. In both instances, a reading of 0 indicates the neutral or non-intervention state (also see Panel 1.4 in Figure 1). The uniform scales of the LTV and SDST intensities set the ordinal sequencing of the successive rounds of policy tightening, from which cardinal information can be derived within the probit regression setting of Equations (1) – (3). The spacing between thresholds in Equation (3), jointly determined by the observed ordering of policy scales and the specified government decision making process, needs not be uniform across the spectrum of policy scales. In Equation (1), it is the continuous policy propensities, not the discrete policy intensities, that enter into the VAR structure to obtain the impulse responses for our analysis.

The set of $r = 4$ referenced variables X_t include the gap between current price and the historical peak in 1997, real median monthly income of households residing in private buildings (available from the General Household Survey), real mortgage interest rates, and the scaled price-rental (available from the Rating and Valuation Department) differential.[4] The HKSAR government has reiterated the importance of using these variables to guide its policy actions.[5] The last variable proxies the rental yield, and, other things being equal, the larger the number, the higher the yield and the less exuberance in the market.

We include in the exogenous variable vector W_t the number of domestic households from the General Household Survey. Household formation, or the change in domestic

[4] The gap between the current price and previous market peak indicates the extent of price excessiveness. Price, mortgage rate, and household income together proxy for buyer affordability. As house price is expressed as an index number rather than a dollar value, direct calculation of affordability is not possible. By the same token, actual rental yield has to make way for a scaled version of the price-rental differential.

[5] See, for example, The HKSAR Government Press Release "LCQ 21: Measures for cooling down the overheated property market and meeting public demand for housing" (December 17, 2014). (http://www.info.gov.hk/gia/ISD_public_Calendar_en.html#)

households, is the main constituent of housing demand, although it is not completely and endogenously determined by property market developments.[6] In the build-up to the modeling specification, the role of external demand is also assessed. The government's Capital Investment Scheme (October 2003-January 2015), Quality Migrant Admission Scheme (June 2006-present), and Admission Scheme for Mainland Talents and Professionals (July 2003-present) are designed to attract investors and talents to Hong Kong. We find that neither an immigration policy dummy nor an income proxy based on Guangdong Province's per capita GDP tend to enhance model validity. This seems to echo the government's claim that foreign demand has lately constituted a relatively small portion of the domestic housing market.[7] These variables are thus omitted.

Income, price, and rentals are all deflated by the composite consumer price index, and mortgage interest rate is expressed in real terms by adjusting for the annualized rate of monthly inflation. The officially quoted real chained values of GDP and capital formation figures are used. All of the data are available monthly, except for the number of domestic households, median household income, and figures in the National Income Accounts, all of which are updated quarterly. We impute the monthly counterparts for these series using the BFL algorithm (Boot, Feibes and Lisman, 1967), which minimizes the sum of squared

[6] We attempted to use population instead of domestic households, and found that the BIC shows virtually identical results. This is not very surprising, as the population and household series have a correlation coefficient of 0.99. More importantly, the HKSAR government has principally relied on the household series to shape their housing policy. See, for instance, the official publications released by the Long-Term Housing Strategy Steering Committee.

[7] According to official statistics, the annual number of immigrants resulting from such policies was less than 0.1% of Hong Kong's population. See the HKSAR Government Press Releases: "LCQ7: Capital Investment Entrant Scheme" (February 23, 2011); "LCQ16: Quality Migrant Admission Scheme" (January 8, 2014); and "LCQ18: Admission Scheme for Mainland Talents and Professionals" (November 24, 2004). (http://www.info.gov.hk/gia/ISD_public_Calendar_en.html#)

first or second differences of the unobserved higher frequency data subject to the constraint that the sum or the average of the imputed components equal to the lower frequency total in the designated time frame. Intuitively, the BFL approach boils down to finding the smoothest curve satisfying the constraint.[8] There is a fair amount of erratic movements in some of the data series, such as transactions and completions. We therefore de-seasonalize all of the data except interest rate, and replace building completion with its 6-month moving averages. Figure 1 shows the major variables in our sample, which contains 240 monthly observations spanning July 1996 to June 2016.

*** Insert Figure 1 here ***

5. Results

5.1 Estimation Results and Assessment

Table 2 is a statistical summary of the MCMC exercise in which we present the posterior estimates of selected parameters and their numerical standard errors. The more robust posterior median is reported instead of the posterior mean, as the large chunk of missing and latent variables may from time to time generate erratic and outlying MCMC draws.

[8] The BFL algorithm, a least-squares approach that technically produces the smallest estimation bias, is a major temporal disaggregation approach that IMF (Bloem *et al.*, 2001) and European Statistical System of EU (European Commission, 2017) have recommended in situations where external referencing data are unavailable. Multiple imputation is an alternative approach to temporal disaggregation when external referencing data are available. To check the robustness of our imputed data to the choice of disaggregation method, we have experimented with applying multiple imputation on the number of domestic households and median household income. The referencing data used include quarterly observations of the working population, the number of unemployed, the number of new leases and tenancy agreements, and a time trend. The quarterly time series imputed from multiple imputation turned out to be highly correlated with those from the BFL algorithm. The correlation coefficients between the two alternative methods are 0.9967 for the number of domestic households and 0.8863 for the median household income.

The two estimates are similar for most of the parameters, but not for the thresholds, which have more variability, as demonstrated by their relatively large standard errors. The standard errors are generally small for most other parameters. All of the coefficients of the first lag terms in the VAR element of the model are positively signed, implying persistence in the underlying data series. The coefficients of the referenced variables in the MOP element are varied. Those for the price gap over the previous market peak and for the proxy rental yield are reasonably signed. Upward price deviation from the previous market peak raises the odds of intervention, whereas higher implied yields dampen the chance of macroprudential tightening. The signs for the other two referenced variables are not conclusive. The estimated MOP error correlation is rather large at $+0.95$, indicating that LTV and SDST policies are likely to be adopted in tandem and as complements.

As aforementioned, the spacing between thresholds in Equation (3) needs not be uniform across the spectrum of policy scales. For instance, according to the estimated thresholds given in Table 2, the LTV policy intensity increases from 0 to 1, and from 1 to 2, if the LTV policy propensity increases from 0 to 0.7248, and from 0.7249 to 1.2085, respectively. This implies that a greater leap in the LTV propensity is required for a tightening of the LTV intensity from 0 to 1 than it is for a tightening from 1 to 2 because the second-round LTV tightening involved only adjustments for the first-round LTV's terms and conditions (see Table 1). By the same token, a greater leap in the SDST propensity is required for a tightening of the SDST intensity from 0 to 1 than it is for a tightening from 2 to 3 because the latter involved only adjustments for the former's terms and conditions.[9]

[9] Figure 4 plots the correlation between the observed intensities and the unobserved propensities of both policy tools.

*** Insert Table 2 here ***

Regarding model validation, we look specifically at the hypothesis of the irrelevance of the ordered probit augmentation and/or policy propensity, i.e., whether the empirical evidence favors a simpler Qual-VAR setup, a simple Bayesian VAR with only observable variables, or the MOP-VAR introduced in this study. The evaluation is done using the extended deviance information criterion (DIC) of Celeux *et al*. (2006) that caters to the incorporation of latent variables and takes into account of both model fit and complexity. The estimated DIC for the MOP-VAR is $-5{,}098.61$ and those of the Qual-VAR and BVAR are $-2{,}829.38$ and $-2{,}620.31$, respectively. Although there is no direct connection between these numbers and their Bayes factors, the evidence ranks the MOP-VAR favorably over the other two benchmarks.

5.2 Generalized Impulse Responses

As our interest lies predominantly in the interrelationships between price, quantity, and policy propensities, we focus our discussion of impulse responses on a few selected shock scenarios that involve these variables. The result is highlighted in Figure 2. Panels 2.1 – 2.3 show the responses of house price, transaction, and building completion to, respectively, a one s.d. shock to LTV propensities and a one s.d. shock to SDST propensities.[10] In contrast to *ex post* observations, Panel 2.1 shows that macroprudential policy shocks do have a negative effect on house prices, but the magnitudes of the effect are more or less negligible. The maximum effect of an LTV shock occurs after two years, with house prices

[10] A one s.d. LTV shock amounts to 0.53 units and a one s.d. SDST shock has a size of about 0.39 units.

declining by about 0.035% at that time. The house price response to an SDST shock is even smaller, but is realized in the first few months of the shock.

Comparing Panel 2.2 with 2.1, the negative impact of LTV and SDST tends to be stronger and more instantaneous on transactions than on prices. Transactions drop abruptly by over 0.6% within the first half-year of a LTV shock and return to the pre-shock level after two years. The full effect of an SDST shock is smaller and dissipates in about one year. While the responses of property trading to both policy shocks are negative, the response to the LTV shock has a larger magnitude.

*** Insert Figure 2 here ***

In Panel 2.3, the effect of the two policy shocks on building completion somewhat diverge. An SDST shock has a positive effect on completion, whereas an LTV shock has a mild negative effect. The effect period is short, with most of the responses tapering off in about a year. A possible reason for the different response is the intrinsic nature of the SDST policy, which serves to freeze a portion of supply by speculators in the short to medium term and thus allows developers to hasten construction and/or pre-sales without having to worry too much about price pressure. LTV policy, in contrast, is a demand-side deterrent, as it tightens credit supply for potential house buyers. Developers thus have smaller incentives to speed up production or supply under this condition.

Panels 2.4 and 2.5 of Figure 2 are the price and trading responses to a one-s.d. house price shock and an interest rate shock. A price shock has a lingering effect on house price, and it takes five years to dissolve half of the initial one-s.d. shock of about 7%. This makes sense, given the long wavelength of the local property market cycle. A price shock also leads to a 2-3% decline in trading with little reversion observed over a 5-year span. An interest rate shock has a negative effect on both the price (a maximum of -2%) and transaction (a maximum of about -10%) variables for residential property. Panel 2.6 indicates how the two policy propensities respond to a one-s.d. shock in house price. Both react swiftly and positively to a price shock, with the LTV propensity peaking near the end of the first year and the SDST propensity hitting a maximum in the first few months. The retreat in both is slow, possibly reflecting the vigilance of the authority in combating price excessiveness.

5.3 Conditional Forecasting

Although the LTV ratio is an established macroprudential policy option in Hong Kong, the tightening seen in the post-QE era resulted in higher instead of lower house prices, a turnout that defied the prediction of the impulse responses. The feedback between variables and the tight demand-supply condition could partly account for this, but a thorough analysis is desirable. This subsection looks into this perplexing phenomenon by asking a series of what-if questions. These questions are not arbitrarily selected, but are pinpointed to answer market participants' criticisms of macroprudential tightening in Hong Kong (e.g., Kirke and Lo, 2013). As a falling interest rate may partly offset the effect of macroprudential policies, the policy effectiveness needs to be assessed at a given interest rate level. Therefore, the following questions are of particular interest. Would the development of the housing market be different if the authority had relied solely on LTV policy and not introduced punitive stamp duties (Scenario 1)? Would the situation have been different if only the SDST option had been chosen instead (Scenario 2)? Would the effectiveness of the macroprudential tightening have been enhanced had it not been for the zero-bound interest rates (Scenario 3)? Conditional on the actual house price trend, what would be the most likely policy attitude of the government (Scenario 4)? The answers can be found in Figures 3 and 4.

*** Insert Figures 3 and 4 here ***

A few remarks here should facilitate our understanding of the results. Unlike impulse response analysis, which identifies untangled one-time structural shocks and the corresponding variable responses, conditional forecasting specifies the entire future path for the designated variables (i.e., the counterfactuals) and identifies the endogenous responses and interactions of other variables as the system propagates. Literally, the *ceteris paribus* dictum applies to the former but not the latter. Also, the impulse response functions incorporate the whole dataset and are history independent in our context. Conditional forecasts, in contrast, are history or path dependent in that only a subset of the data is used in the estimation, and thus the forecasts based on the same preset conditions may differ when the time instance of prediction changes.

Panels 3.1 and 3.2 in Figure 3 show the prediction under Scenario 1. The partial intervention involves only LTV tightening, with the SDST status being unaltered from December 2010 onward. In this scenario, house prices rise along an elevated trajectory and trading activities are substantially higher by mid-year 2016. The various notions of punitive stamp duty impose a *de facto* transaction cost on speculative short-term trading and on owning a second property. Removing such cost thus allows a more buoyant market and higher house prices as different investors reap the full benefit of the low-interest-rate environment.

Panels 3.3 and 3.4 depict the situation of Scenario 2, where the tightening track of SDST from August 2010 is unrestrained but the LTV policy is frozen from that date. This results in an absence of certain types of market participant and very subdued trading, as expected. The conditioned policy stance also initially drives prices higher. A plausible explanation for this is that the relatively lax LTV policy lifts the financial restraint on buyers seen in Scenario 1. For instance, owner-occupiers who intend to trade up the housing ladder are less hesitant to sell their current property, as they know that the future mortgage condition will not toughen up. This upward trend reverses in about three years, and house prices then enter a phase of moderate but prolonged correction. The findings, displayed in Scenario 2, are strikingly consistent with the predictions of Ortalo-Magne and Rady's (2006) theoretical model. In their model, relaxing home buyers' credit constraints increases first-time buyers' ability to afford the down payment on starter homes, and thus drives the starter home prices upward. The resulting capital gains on starter homes enable their owners to afford the down payment for trade-up homes, which may in turn cause an overreaction of house prices. However, the capital gains on starter homes will subsequently disappear and the demand for trade-up homes will shift back down as home buyers' incomes stabilize. According to Ortalo-Magne and Rady (2006), this capital gain mechanism may explain why house prices could have overreacted and then entered a phase of correction if the HKSAR government had frozen LTV in 2010 under Scenario 2. Apparently, the impact of LTV on house prices was dynamically more complicated and uncertain than what the government expected. Over a longer horizon, such an impact is not unambiguous.

Panels 3.5 – 3.6 give the prediction under Scenario 3, where the real mortgage rate is fixed at pre-2007 levels (constant from June 2007 onward). The authority's policy propensities are left unrestricted. In this scenario, prices experience an upward trend that is less elevated and acute than the real-world trend, and by mid-year 2016 house prices are about 20% less than in the real world. Transactions are more or less the same as in the observed trend, although there are fewer twists and turns along the way.

Although Scenario 3 unambiguously suggests that macroprudential policy in Hong Kong has a more pronounced negative impact on house prices when the real interest rate remains stable, a comparison of Scenarios 1 and 2 reveals that SDST rather than LTV is more likely to trigger a trend reversal in house prices over the longer term. Despite the HKSAR government's preference for LTV as its major instrument, our findings imply that any further policy tightening, if any, should focus on a combination of stamp duty and stress test (i.e., SDST) rather than on LTV.

Figure 4 shows the outcome of Scenario 4. Strictly speaking, this is not counterfactual *per se*, but is a revelation of the model-implied policy propensities given the actual trends in house price. It is evident that surging house prices lift both the LTV and SDST policy propensities, a result consistent with the actual macroprudential tightening (the increasing policy intensities). Therefore, the interaction of house price and macroprudential policy is not unidirectional, and there is a solid chance that tightening policy may persist for a long time if the house price response to the initial tightening is either slow or small. A subtle observation is that policy intensities and policy propensities are non-linearly related. Although the step size of the former is 1 by definition, that of the latter varies over different stages of policy tightening.

In general, the observations from the first three scenarios affirm the dampening effect of macroprudential policy on house prices and trading activity. The exact price and quantity behavior hinges upon the policy mix being used and the concurrent development of other endogenous factors. The last scenario highlights the pull of house prices on macroprudential tightening. Lessons learned include the following: (i) macroprudential tightening may decrease the elevation of the price trend instead of reverting it, and (ii) the tightening would have been more successful and effective had interest rates not hit such unprecedented low levels.

5.4 Unconditional Forecasting

We conclude our analysis with a final step of model checking. In this subsection, we use the methods in Dueker (2005) to evaluate the model's ability to conduct out-of-sample forecasts. That is, we focus on the probabilistic forecasts of possible policy regime changes instead of on the forecast accuracy of observables.[11] This is not uncommon among models with latent variables, such as hidden Markov models. It is important to note that conventional models (e.g., Qual-VAR) are not directly comparable to our MOP-VAR approach because the latter provides probabilistic forecasts of policy intensity changes that are not available in the former. Pragmatically, the timing of policy changes is of utmost importance to decision makers such as home buyers and sellers, and this is where the MOP-VAR has an edge over competing models.

[11] The forecasating exercise of Dueker (2005) is not done recursively and concentrates instead on a single out-of-sample period during which there are *ex post* regime changes. It assesses how well the Qual-VAR foretells the realization of dichotomous states.

The out-of-sample forecasting exercise is conducted using an end-sample estimation of the MOP-VAR up to June 2012 and a forecast horizon that covers the next 12 calendar months. Forecasts one to twelve steps ahead are computed correspondingly. This 12-month timeframe is selected due to the multiple changes observed in both the LTV and SDST. Unlike Dueker (2005), where the latent variable is dichotomous, our policy variables are categorical, and this makes the classification of future regime changes less straightforward. As an illustration, the last recorded value of LTV in the end-sample is four, which is among the highest values seen between July 1996 and June 2012. Suppose the forecast LTV policy *propensity* edges higher in the subsequent 12 months; given the information in the end-sample, all we know is that the policy *intensity* may stay the same (within category 4) or climb to higher levels (categories 5, 6, or higher) because the thresholds in (3) for levels above category 4 are not defined without a full-sample estimation. The Qual-VAR has no such problem, as the threshold for the dichotomous variable is precisely defined at 0.[12]

We sidestep the issue by using information about the gap between the two largest thresholds $\delta = (c_{imax}/c_{imax-1}) - 1$ of each latent variable and consider the following: (i) a DOWN case if the forecast propensity is smaller than $1 - 2\delta$ of the last end-sample value, and (ii) an UP case if the forecast propensity is larger than $1 + 2\delta$ of the last end-sample value. As both the propensity and threshold figures vary in each iteration, the two cases provide a fair range for us to gauge the tendency towards a *notable* change in policy intensity. The findings are summarized in Table 3, where comparable figures from a benchmark Qual-VAR are also presented.

[12] The problem raised here is not inherent in the methodology but is purely a data problem. If our end-sample contains episodes of tightening and relaxation, categorizing forecast propensities is straightforward.

*** Insert Table 3 here ***

For the LTV, the median unconditional forecast for the first month jumps markedly from the last value of the end-sample and the predicted values rise steadily over the entire forecast horizon. The probability of a notably intensified LTV policy is well above 70% and rises gradually at the approach of the actual policy change date of September 2012. Although it peaks around October of that year and retreats somewhat before the second policy change date of March 2013, the overall probability remains above 70% and dwarfs the likelihoods of other counter-scenarios. The situation of SDST is slightly different. There are three relevant policy change dates—September 2012, November 2012, and March 2013. The median forecast of SDST propensity starts out with a rather sharp jump from the end-sample level and shows a mildly inverted U-shaped pattern over the forecast horizon. Meanwhile, the probability of a notable policy change is high and above 50% throughout. Unlike the LTV counterpart, the UP probability rises continuously past the first two policy change dates and peaks near the third date of March 2013. In sum, the predicted probabilities make rather accurate calls for SDST tightening and slightly less so for the LTV. The assessment of regime changes is not straightforward given our data, but with proper manipulation of the hidden information, the model can rather accurately date the changes.

In comparison, the Qual-VAR policy variable has a natural threshold of 0, above which the presence of a macroprudential regime is signified (state-1) without regard to the specific tools being adopted. From Table 3, the probability of state-1 equals 1 as we move into the first month beyond the end-sample, and it edges down gradually over the remaining 11 months. We can see that the very high state-1 likelihood matches the persistence of the macroprudential policy that is actually realized, but the variations in the probability over time seem to be at odds with the gradual intensification of the policy. As mentioned above, MOP-VAR and Qual-VAR are not directly comparable in this regard because the latter provides no information on probabilistic changes of policy intensities.

In terms of house price forecast, the MOP-VAR and Qual-VAR produce similar results: predicted 12-month growths of 3.5% and 4%, respectively. The caveat is that these are one-shot predictions and are not suggestive of forecast accuracies typically measured in a recursive manner. Furthermore, these figures do not account for the differences in model complexity and the possible larger variances associated with the larger set of latent variables in the MOP-VAR.

6. Conclusions

This study evaluates the effectiveness of Hong Kong's macroprudential policy in stabilizing the housing market. We focus on two forms of tightening in this study: lowering the loan-to-value ratio and introducing punitive stamp duties and stress tests. Their effects are analyzed by way of a multivariate ordered probit-augmented vector autoregressive model (MOP-VAR) which allows explicit measurement of policy intensities. Prominent features of MOP-VAR include capturing possible endogeneity among the intensities of various macroprudential policy instruments and facilitating a comprehensive analysis of the bilateral relationship between asset prices and those instruments. In addition, it provides probabilistic forecasts of future changes in macroprudential policy intensities that conventional approaches cannot accomplish. The convenience of using categorical policy variables is particularly obvious when conducting counterfactual analysis at different time points and with different contemporary policy statuses.

The identified impulse responses from our exercise show that the negative impact of macroprudential policy is stronger and more instantaneous on transactions than on prices. Indeed, the strong and prolonged own response to a house price shock can more than offset the policy-induced decline in house prices. Another factor that masks the effectiveness of macroprudential tightening is the zero-bound interest rates that have prevailed in recent years. Our empirical evidence shows that house prices would have been lower in the wake of the tightening had mortgage rates stayed at their pre-crisis levels, although this would be manifested in the form of a lessened price trend instead of a trend reversion. The results of the conditional forecasting exercise reveal that, over the long haul, a combination of stamp duty and stress test tends to be more effective in triggering a trend reversal in house prices, despite the government's preference of using the loan-to-value ratio to achieve this goal.

Compliance with Ethical Standards:

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Appendix: Estimation Algorithm

- Stacking the observations and reorganizing the algebra of the VAR in (1) gives

$$\tilde{Y} = \tilde{X}H + U,$$

where $\tilde{Y} = [\tilde{Y}_1, \cdots, \tilde{Y}_T]'$ and $U = [u_1, \cdots, u_T]'$ are both $T \times (m+q)$; $\tilde{X}$ is the $T \times (n + (m+q)p)$ matrix of the conforming exogenous and lagged variables; and $H = [B\ A_1 \cdots A_p]'$ is the $(n + (m+q)p) \times (m+q)$ coefficient matrix. The Minnesota prior assumes the following distribution on $h = vec(H)$:

$$h \sim N(\mu_h, V_h),$$

where μ_h is a vector of zeros except for the elements corresponding to the first own lag of $\tilde{Y}$ that equals one. The prior variance V_h is a diagonal matrix with the elements

$$\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \text{ if } i = j \text{ and } \quad \left(\frac{\sigma_i \lambda_1 \lambda_2}{\sigma_j l^{\lambda_3}}\right)^2 \text{ if } i \neq j$$

for lag l of the j^{th} variable in the i^{th} equation. σ_i is the OLS estimate of the standard deviation of the i^{th} error term. The prior variances of other exogenous variables are λ_4. We set $\lambda_1 = 0.1,\ \lambda_2 = 0.25,\ \lambda_3 = 2$, and $\lambda_4 = 10000$. The VAR order is $p = 2$.

- Let D denote data, Θ the set of all of the parameters $\{h, \Sigma, \beta, \rho, Y_t^*, c_{ik}\}$, and $\Theta_{\backslash a}$ the subset of Θ excluding a. Assuming a conjugate inverted-wishart prior for the VAR covariance matrix Σ, the conditionals $f\left(h|\Theta_{\backslash h}, D\right)$ and $f\left(\Sigma|\Theta_{\backslash \Sigma}, D\right)$ are normal and inverted-wishart, respectively.

- The probit regression coefficient β has a normal prior with a mean and variance set to the OLS estimates of the corresponding univariate ordered probit models. Gibbs sampling from the conditional $f\left(\beta|\Theta_{\backslash \beta}, D\right)$ is straightforward. We assume the variance of ε_t has the form $\Omega = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$ with $|\rho| < 1$ to ensure that the matrix is positive semidefinite. MCMC updates of ρ are calculated from the simulated outcomes of $\hat{\varepsilon}_t$. For consistency, we normalized the coefficient vector β correspondingly.

- For each $i = 1, \cdots, q$, the K_i thresholds can be drawn recursively from uniform conditionals given the assumed diffuse priors:

$$f\left(c_{ik}|\Theta_{\backslash c_{ik}}, D\right) = U\left(\max\left(\max_{y_{it}=k-1}(y_{it}^*), c_{ik-1}\right), \min\left(\min_{y_{it}=k}(y_{it}^*), c_{ik+1}\right)\right).$$

We find that the mixing of the chain improves with shrewdly chosen upper and lower threshold bounds. After numerous trials, we set those at $-19 < c_{1k} < 199$ and $-9 < c_{2k} < 19$, which are wide enough to accommodate their respective OLS estimates.

- Sampling of Y_t^* is more complicated. To begin, we partition the elements of the VAR in the following manner (we assume an order $p = 2$ in the illustration):

$$\tilde{Y}_t = \begin{bmatrix} Z_t \\ Y_t^* \end{bmatrix}, \quad u_t = \begin{bmatrix} u_{Zt} \\ u_{Yt} \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \Sigma_{ZZ} & \Sigma_{ZY} \\ \Sigma_{YZ} & \Sigma_{YY} \end{bmatrix},$$

with conforming coefficient matrices $B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}$ and $A_j = \begin{bmatrix} A_{j1} & A_{j2} \\ A_{j3} & A_{j4} \end{bmatrix}, \forall j$. B_1 and B_2 have respective dimensions of $m \times n$ and $q \times n$; A_{j1} is $m \times m$; A_{j4} is $q \times q$; and A_{j2} and A_{j3} are $m \times q$ and $q \times m$, respectively. Now,

$$Z_t = B_1 W_t + [A_{11}\ A_{12}] \begin{bmatrix} Z_{t-1} \\ Y_{t-1}^* \end{bmatrix} + [A_{21}\ A_{22}] \begin{bmatrix} Z_{t-2} \\ Y_{t-2}^* \end{bmatrix} + u_{zt} \quad \text{and} \quad (A1)$$

$$Y_t^* = B_2 W_t + [A_{13}\ A_{14}] \begin{bmatrix} Z_{t-1} \\ Y_{t-1}^* \end{bmatrix} + [A_{23}\ A_{24}] \begin{bmatrix} Z_{t-2} \\ Y_{t-2}^* \end{bmatrix} + u_{Yt}. \quad (A2)$$

Let $\mu_{Zt} = B_1 W_t + A_{11} Z_{t-1} + A_{21} Z_{t-2}$ and have μ_{Yt} similarly defined for terms in (A2). Together with equation (2) in the main text, we can rewrite the system in state space form:

$$\begin{bmatrix} Y_t^* \\ Y_{t-1}^* \end{bmatrix} = \begin{bmatrix} A_{14} & A_{24} \\ I_q & 0 \end{bmatrix} \begin{bmatrix} Y_{t-1}^* \\ Y_{t-2}^* \end{bmatrix} + \begin{bmatrix} \mu_{Yt} \\ 0 \end{bmatrix} + \begin{bmatrix} u_{Yt} \\ 0 \end{bmatrix} \text{ and} \quad (A3)$$

$$\begin{bmatrix} Z_t - \mu_{Zt} \\ (I_q \otimes X'_{t-1})\beta \end{bmatrix} = \begin{bmatrix} A_{12} & A_{22} \\ I_q & 0 \end{bmatrix} \begin{bmatrix} Y^*_{t-1} \\ Y^*_{t-2} \end{bmatrix} + \begin{bmatrix} u_{Zt} \\ -\varepsilon_{t-1} \end{bmatrix}, \qquad (A4)$$

where the 0s have conforming dimensions.

- The Kalman filter (KF) is then applied to (A3) and (A4) in the forward filtering stage with the outcome being stored and used in the subsequent stage of backward smoothing/sampling. A few remarks are warranted. First, a normal prior is assumed for the initial state vector $[Y_0^{*\prime}, Y_{-1}^{*\prime}]'$. Second, the error terms in the transition equation (A3) and the measurement equation (A4) are not independent, as in standard KF application, because Σ_{YZ} is not a null matrix. So, modifications to the KF recursion (e.g., Ma *et al*., 2010) have to be used to account for the correlation between measurement and transition noises. Finally, the drawn values of the latent variables have to obey the inequality constraints instigated by the thresholds c_{ik} and the observed categorical data y_{it}. Simon (2010) suggests a few ways to resolve the issue and we accomplish this by adding an extra constrained minimization step after getting the updated state estimates from the unconstrained forward filter and backward smoother.
- In sum, the algorithm iterates through the normal-inverted-wishart conditionals for the VAR components, a normal conditional for the probit coefficients and the derived computation of the cross-correlation of the latent variables, uniform conditionals for the thresholds, and a constrained KF update and backward sampling of the latent variables. The simulation runs for 8,000 loops with the last 4,000 used to compute the posterior estimates.

Table 1. Chronology of Major Macroprudential Policy Tightening in Hong Kong

Round	*Date*	*Loan-to-value (LTV) Ratio*	*Policy Intensity Indicator*	*Date*	*Special Stamp Duty (SSD), Double Stamp Duty (DSD) and Stress Test*	*Policy Intensity Indicator*
0	Before Nov 2009	70% for all properties.	0	-	-	0
1st	Nov 2009	60% for V≥$20m; 70% for V<$20m.	1	-	-	
2nd	Aug 2010	60% for V≥$12m; 60% for non-owner occupied properties.	2	Aug 2010	Stress Test: Mortgage rate +2%; Maximum stress DSR 60%.	1
3rd	Dec 2010	50% for V≥$12m; 60% for $12m>V≥$8m; 70% for V<$8m; 50% for non-owner occupied, company held, commercial & industrial properties with net-worth based mortgages.	3	Dec 2010	SSD: 15% for M ≤6 months; 10% for 6 months< M ≤12 months; 5% for 12 months< M ≤24 months.	2
4th	Jun 2011	50% for V≥$10m; 60% for $10m>V≥$7m; 70% for V<$7m; 50% (base) for non-owner occupied, company held, commercial & industrial properties; 40% (base) net-worth based mortgages; 10% lower for all cases with incomes from outside Hong Kong.	4	Sep 2012	Stress Test: Mortgage rate +2%; Maximum stress DSR 50%.	3
5th	Sep 2012	30% (base) net-worth based mortgages; 20% (previously 10%) lower for all cases with incomes from outside Hong Kong.	5	Nov 2012	SSD: 20% for M ≤6 months; 15% for 6 months< M ≤12 months; 10% for 12 months< M ≤24 months; 10% for 24 months< M ≤36 months. Buyer Stamp Duty (BSD): 15%.	4
6th	Mar 2013	10% lower (from the previous level) for all non-owner occupied and non-residential properties; 40% for standalone carparks.	6	Mar 2013	DSD: Maximum 8.5% for V≥$2m applying to all properties except first home. Stress Test: Mortgage rate +3%.	5
7th	Mar 2015	60% for V<$7m and self-use properties.	7	Mar 2015	Stress Test: Maximum stress DSR 50% for self-use second properties and non-self-use properties.	6

Remarks: V is the property value; M is the number of months between the dates of acquisition and disposal (resale or transfer); DSR is debt-service-ratio; SSD is levied on short term trades; BSD is levied on trades involving non-local buyers; DSD is levied on transactions involving second homes and non-residential premises. All monetary values are denominated in HK$. The above information was extracted from press releases of the HKSAR government and HKMA. The 8th round of tightening in November 2016 is not included in the sample due to information lag of property market data.

Table 2. Summary of the MCMC Estimation and Validation

Parameters	*Posterior Median*	*Numerical s.e.*	*Parameters*	*Posterior Median*	*Numerical s.e.*
VAR Coefficients of 1-st Own Lag of Equation			Diagonal Elements of VAR Covariance Matrix		
House Price	0.9943	0.0035	House Price	0.0048	0.0001
Transactions	0.7405	0.0094	Transactions	0.0625	0.0025
Completion	0.7813	0.0061	Completion	0.0340	0.0004
Mortgage Rate	0.9717	0.0099	Mortgage Rate	0.0043	0.0000
Non-housing Output	0.9934	0.0074	Non-housing Output	0.0043	0.0000
LTV	0.4874	0.0906	LTV	0.1803	0.0720
SDST	0.5839	0.1415	SDST	0.2591	0.1706
Thresholds for LTV Propensity			Thresholds for SDST Propensity		
c_{11}	0.7248	0.3785	c_{21}	1.0100	1.4396
c_{12}	1.2085	0.3086	c_{22}	1.0761	1.4304
c_{13}	1.2750	0.3019	c_{23}	1.4009	1.3931
c_{14}	1.3699	0.3016	c_{24}	1.4668	1.3872
c_{15}	1.6186	0.3252	c_{25}	1.5683	1.3882
c_{16}	1.7451	0.3390	c_{26}	2.1147	1.4354
c_{17}	2.2690	0.3741			
MOP Coefficients for LTV			MOP Coefficients for SDST		
Gap from Peak	0.0476	0.0001	Gap from Peak	0.1087	0.0008
Mortgage Rate	−0.0001	0.0000	Mortgage Rate	0.0051	0.0001
Household Income	0.1386	0.0001	Household Income	0.0916	0.0001
Price-Rent Differential	−0.0111	0.0001	Price-Rent Differential	−0.1833	0.0015
LTV-SDST Correlation					
ρ	0.9516	0.0158			
Deviance Information Criterion			Absolute Value of VAR Eigenvalues		
MOP-VAR	−5098.61		Maximum	0.9875	
Qual-VAR	−2829.38		Minimum	0.0008	
BVAR	−2620.31				

Remarks:
(1) The esimtates and numerical standard errors are computed using 4,000 posterior iterations upon another 4,000 warm-up iterations in the Markov chain Monte Carlo exercise.
(2) LTV stands for loan-to-value ratio policy while SDST indicates the combination of stamp duty and stress test policy.

Table 3. Summary of Out-of-sample Forecasting

	MOP-VAR								***Qual-VAR***		
	LTV				*SDST*				*Qual-VAR Policy*		
Date	*Median Forecast*	*Actual Intensity*	*Prob. of DOWN*	*Prob. of UP*	*Median Forecast*	*Actual Intensity*	*Prob. of DOWN*	*Prob. of UP*	*Median Forecast*	*Actual Intensity*	*Prob. of State-1*
End-sample											
June 2012	12.578	4			2.870	2			0.127	1	
Out-of-sample											
July 2012	13.637	4	0.000	0.768	3.199	2	0.214	0.556	0.728	1	1.000
August 2012	13.951	4	0.001	0.803	3.230	2	0.255	0.579	0.848	1	0.999
September 2012	14.247	5	0.002	0.811	3.366	3	0.276	0.584	0.969	1	0.998
October 2012	14.479	5	0.005	0.812	3.425	3	0.282	0.586	1.067	1	0.996
November 2012	14.701	5	0.012	0.807	3.467	4	0.286	0.589	1.116	1	0.992
December 2012	14.869	5	0.023	0.798	3.457	4	0.286	0.589	1.120	1	0.982
January 2013	15.055	5	0.037	0.787	3.456	4	0.288	0.591	1.119	1	0.967
February 2013	15.225	5	0.049	0.773	3.443	4	0.289	0.592	1.108	1	0.950
March 2013	15.359	6	0.068	0.762	3.424	5	0.290	0.589	1.092	1	0.930
April 2013	15.499	6	0.087	0.751	3.426	5	0.290	0.596	1.077	1	0.910
May 2013	15.635	6	0.101	0.741	3.411	5	0.290	0.586	1.071	1	0.892
June 2013	15.815	6	0.117	0.732	3.387	5	0.292	0.586	1.056	1	0.873

Remarks:

(1) The in-sample runs from July 1996 to June 2012. The out-sample runs from July 2012 to June 2013. The forecasts are obtained by propogating the model forward month by month based on 1-step forecasts.

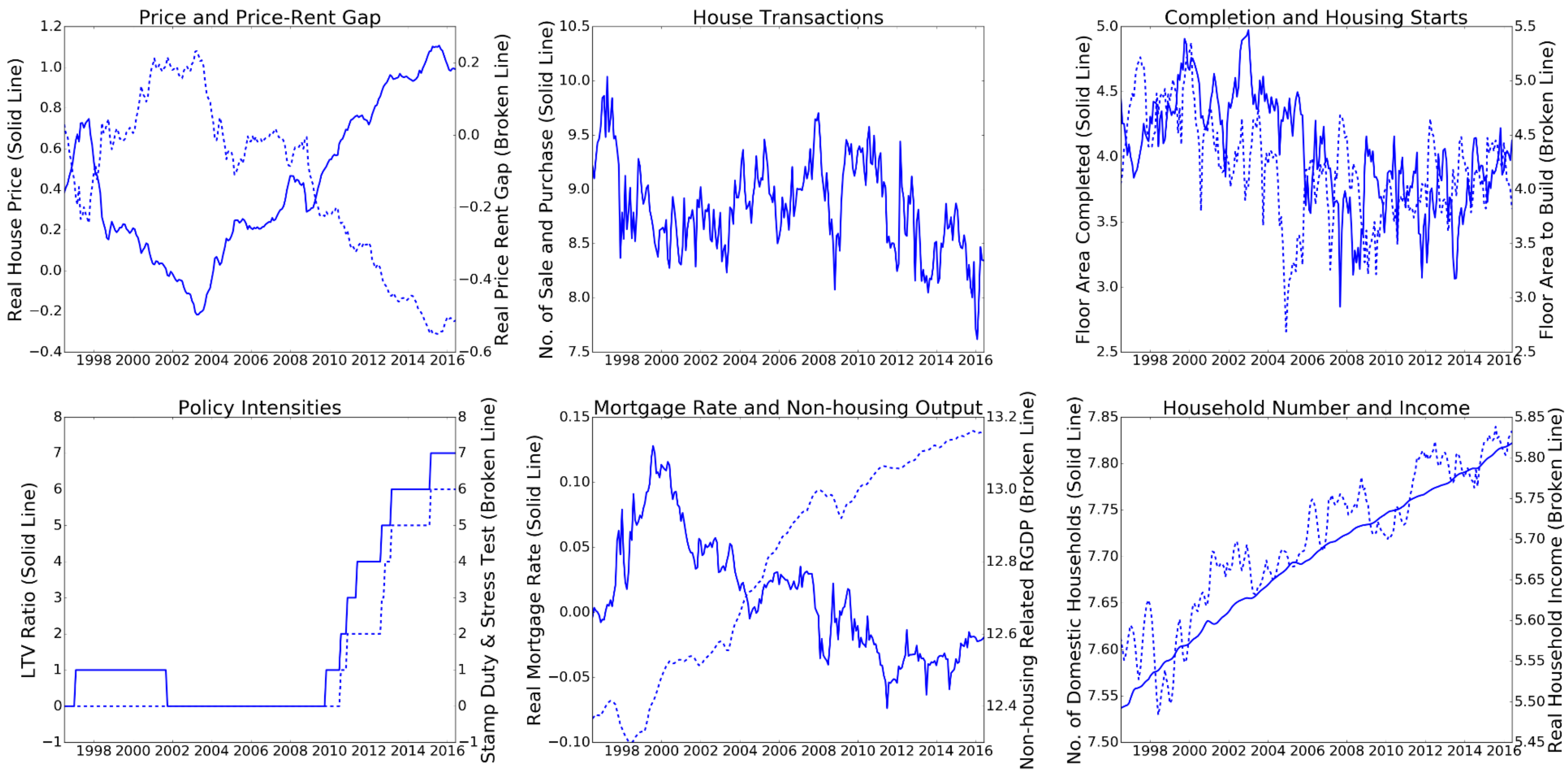
(2) LTV stands for loan-to-value ratio policy while SDST indicates the combination of stamp duty and stress test policy.

(3) The forecast values are the unobserved policy propensities and the categorical policy intensities are those actually observed.

(4) State-1 of the Qual-VAR model indicates the presence of macroprudential policy tightening.

Figure 1. Housing Market Data and Macroprudential Indicators in Hong Kong

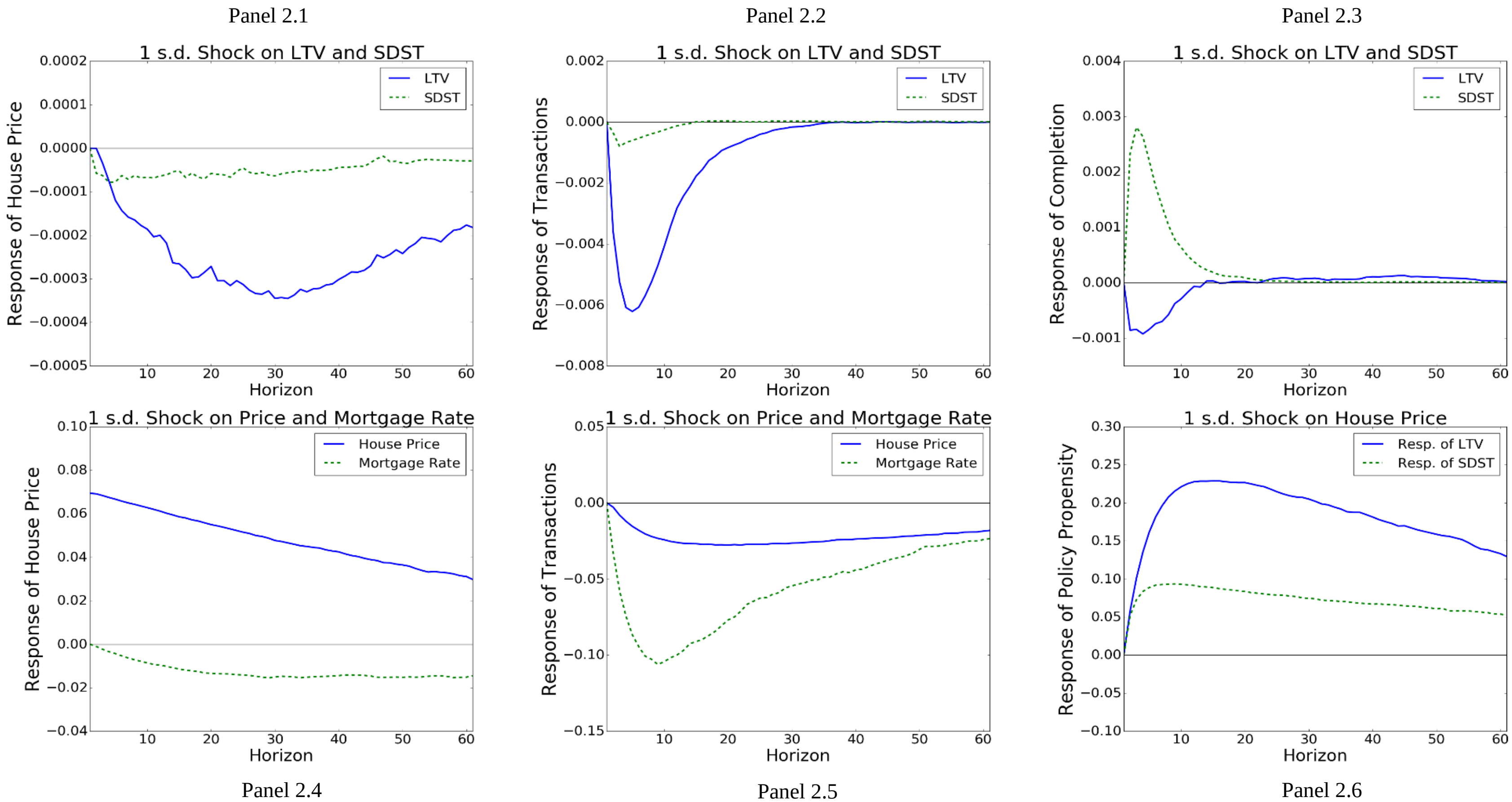
Panel 1.1 Panel 1.2 Panel 1.3



Panel 1.4 Panel 1.5 Panel 1.6

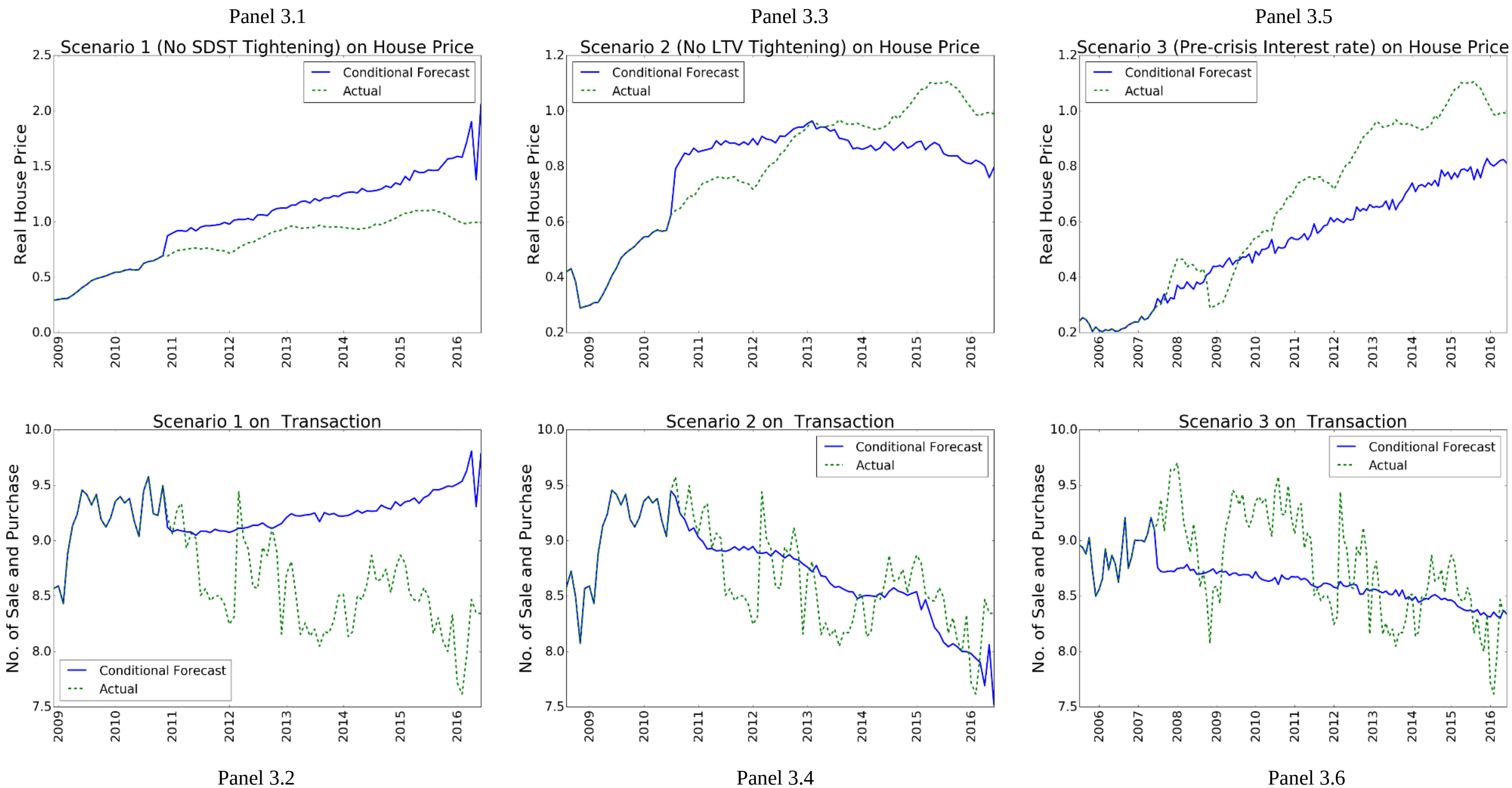
Remarks: All level data are log transformed except for the intensity figures.

Figure 2. Generalized Impulse Response Functions for Selected Shock-Response Scenarios



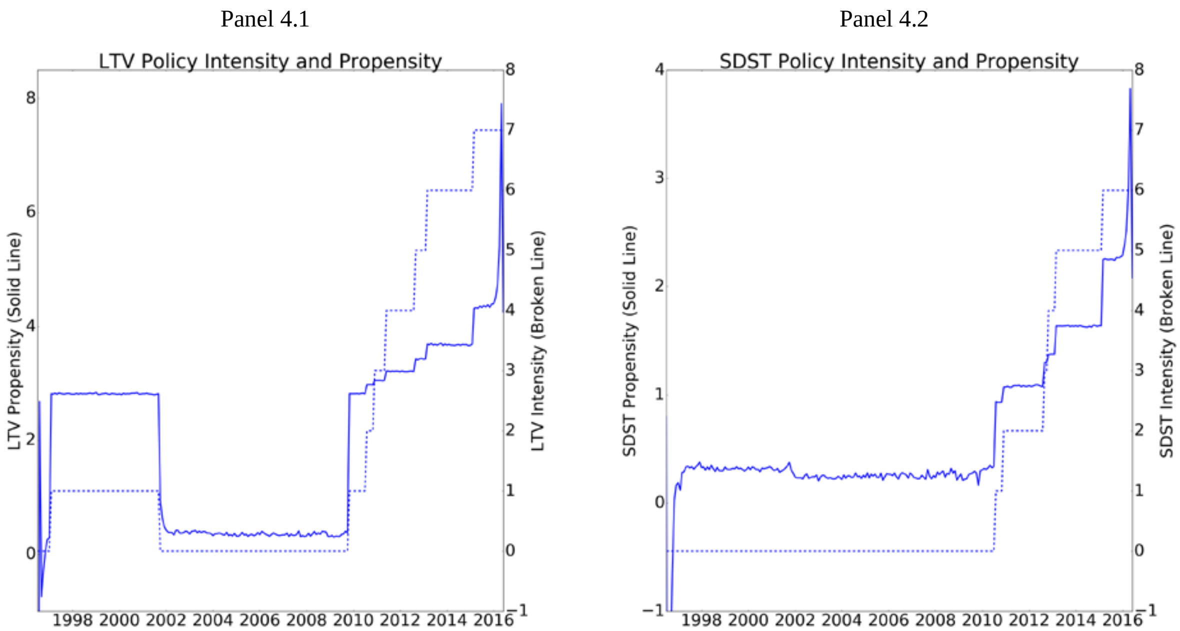
Remarks: The generalized impulse responses are generated from a MCMC sample of 1,000 iterations.

Figure 3. Conditional Forecasts of Price and Transactions Under Various Scenarios



Remarks: Scenario 1 corresponds to the counterfactual where no punitive stamp duty was introduced in Dec. 2010 or later but the LTV policy was tightened as actually happened. Scenario 2 assumes SDST tightening from Aug. 2010 as actual but LTV was frozen at the mild level recorded before that date. Scenario 3 corresponds to the case where macroprudential policy was tightened as actually happened but the mortgage rate was kept at the pre-crisis level (as of Jun. 2007).

Figure 4. Conditional Forecasts of Policy Propensities under Scenario 4



Remarks: Scenario 4 corresponds to the case where house price followed its actual trend. The diagrams show the forecasts of the unobserved policy propensities (solid lines) of the government in response to such a development. The actual policy intensities (broken lines) are appended for comparison