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Inter-DRG Resource Allocation in a Prospective Payment System: A Stochastic Kernel Approach*

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Abstract

This paper empirically investigates the distribution dynamics of resource allocation decisions across Diagnosis Related Groups (DRGs), in a continuing Prospective Payment System (PPS) . The theoretical literature suggests a PPS could lead to moral hazard effects, where hospitals have an incentive to change the intensity of services provided to a given set of patients, a selection effect whereby hospitals have an incentive to change the severity of patients they see, and thirdly hospitals could change their market share by specialization (practice style effect). The related econometric literature has mainly focussed on the impact of PPS on average Length of Stay (LOS) concluding that the average LOS has declined post PPS. There is little literature on *distribution* of this decline across DRGs, in a PPS. The present paper helps fill this gap. The paper models the evolution over time of the empirical distribution of LOS across DRGs. The empirical distributions are estimated using a non parametric "stochastic kernel approach" based on Markov Chain theory. The results suggest that relative prices of DRGs are one of the determinants in resource allocation across DRGs. In addition, a reduction in the high outlier episodes indicates existence of potential selection effect even in a continuing PPS.

1 Introduction

The empirical analysis of the impact of prospective payment systems (PPS) or case-mix funding on the resource allocation in hospitals has received widespread attention in recent years. Under a PPS, hospitals are paid lump sum per admission. The main objective of introducing PPS is to improve hospital efficiency (For example in Australian State of Victoria case-mix funding was introduced to reduce health expenditure while maintaining service outputs). A PPS regime enables payers (health department) and providers (hospitals) to share the financial risk of patient care. Such a sharing mechanism is also termed as "supply side cost sharing" by Ellis and McGuire (1993).

The theoretical models (see for example, Selden (1990); Newhouse (1996); Ellis and McGuire (1996); Siciliani (2006)) that underlie these works can be classified into three broad categories. Firstly, case-mix funding could lead to a moral hazard effect where hospitals have an incentive to change the intensity of services provided to a given set of patients. Secondly the reimbursement mechanism could lead to a selection effect whereby hospitals have an incentive to change the severity of patients they see, and thirdly in a competitive setup the hospitals could change their market share by specialization (practice style effect).

It has been argued in the literature that a fully prospective payment system leads to technical efficient production of health care as the hospitals keep the difference between the payment per episode and cost of treating a patient. Thus unlike a cost reimbursement system (where hospitals attempt to obtain maximum reimbursement by treating the patient with maximum intensity) hospitals will not have an incentives to over provide a service due to rent in factor prices (Newhouse, 1996). Although PPS encourages hospitals to produce efficiently it also increases the likelihood of patient selection thereby denying some patients the treatment they desire. Thus there exists a tradeoff between selection and production efficiency (Ma, 1994). Such a "selection-efficiency" tradeoff has been extensively discussed in a review by Newhouse (1996). One of the major implications of such a tradeoff could be under servicing of high cost patients[1] (Newhouse, 1983, 1996; Selden, 1990). Under a PPS the marginal revenue to treat a high cost patient is likely to be less than the marginal cost

[1]Here high cost patients refer to the patients having relatively higher cost within the distribution of costs of an individual DRG.

of the treatment and thus hospitals will have an incentive to under service such patients. Newhouse (1996) and Newhouse (2002) discuss several theoretical frameworks addressing the issue of selection from the perspective of the supply side of health care. However, Newhouse (1996) observes that such theoretical frameworks have limited capabilities in terms of empirical work. This is mainly because of their requirement for information on unobservable variables viz. information on a hospital manager's utility function for effort, unobserved patient factors affecting cost, the physicians utility function and error variances in the prices etc. In addition, most of the assumptions in these models are untestable.

Most of the earlier econometric research on PPS has tried to estimate its effects by analysing the length of stay (LOS) data for different Diagnostic Related Groups (DRGs). For example, in making a case for selection effect Newhouse and Byrne (1988) argue that some of the decline in LOS after PPS is caused by the shift of more severe cases to facilities not paid by PPS. Most of the empirical evidence is on the effect of a switch to PPS regime on LOS and the general consensus is that the average LOS per discharge at hospitals has declined after the introduction of PPS (Freiman et al., 1989; DesHarnais et al., 1990; Manton et al., 1993; Ellis and McGuire, 1996; Norton et al., 2002).

Although PPS led to a relative reduction in LOS for inpatients, the potential imperfections in the funding regime could offset to a certain extent the very achievements of PPS. One such example is per diem payment for a patient with unusually long LOS. In a PPS, the inpatient hospital discharges are coded into DRGs (which are based on clinical relevance and resource homogeneity). Further, at the beginning of the financial year, each DRG is assigned a weight to reflect its relative resource consumption in the penultimate year. The count of inpatient output is then derived by multiplying each inpatient discharge by the relevant DRG weight. For each DRG, low and high trim points are set to determine unusually short stay (low outlier) and unusually long stay (high outlier) patients. The inpatient episodes with LOS between the trim points are called inliers. Hospitals are paid extra for high outliers. For example in Australian State of Victoria (a pioneer in DRG based funding going back to 1993), high outliers receive additional weight for *each day* above the high trim point.

It has been argued that such "imperfections" in hospital funding might introduce the incentives for hospitals to increase expenditure and maximize reimbursement thereby partially offsetting the anticipated effect of PPS (Norton et al., 2002). Moreover, even a continuing PPS regime might induce such hospital behaviour because of temporal changes in the relative DRG weights which are used for funding inpatient episodes in the hospitals. For example, in Victoria, relative DRG weights are highly volatile up to the extent of +10% to -10% per year. Such volatility in DRG weights might lead to incentives for hospitals to assign patients to profit making DRGs ("DRG-creep") or split a patient into several cases ("patient splitting") in order to maximise funding for that particular inpatient episode.

Similarly, the hospitals might redistribute their resources to more lucrative patients and discharge less lucrative patients "quicker and sicker" (which could result in increasing readmission rates). It should be noted that the definition of a lucrative DRG might change in each time period (based on its relative weight) and thus the resources need to be again redistributed to maximize government reimbursement[2]. Hence it is imperative to simultaneously consider the cross-sectional (across DRGs) and dynamic (over years) behaviour of resource allocation.

Thus an empirical framework to test the distribution dynamics of resource allocation decisions across DRGs in a PPS is critical from a policy point of view. Such an analysis reflects on the efficacy of case-mix policy and will be of interest to policy makers. For example, the conclusions from such an analysis might shed light on the perception that high cost patients are underserviced or changes in relative price of DRGs is one of the factors responsible for resource allocation decisions across DRGs.

The main objective of this paper is to empirically investigate the distribution dynamics of resource allocation decisions across DRGs, in a continuing PPS regime. As discussed earlier, the extant literature has mainly focussed on the impact of introduction of PPS on average LOS by comparing the pre/post PPS scenarios and concluded that the average LOS has declined post PPS. However, there is little literature on *distribution* of this decline in LOS across DRGs, in a continuing PPS regime. The present paper intends to help fill this gap. In a continuing PPS regime, the hospitals might be less inclined to reduce

[2]This argument is particularly valid for elective non-urgent episodes of patient care which are funded under PPS. Thus only such episodes are considered for empirical analysis in this paper.

LOS in "lucrative" DRGs and hence the overall reduction in LOS might be a result of disproportionately higher reduction in less "lucrative" DRGs[3]. This paper proposes an empirical framework to test for such a behaviour by explicitly analysing the temporal changes in the re-distribution of resources, in a continuing PPS regime.

The empirical methodology models the evolution over time of the empirical distribution of length of stay across DRGs. The main purpose of this is to record not only the mean and variance of the distribution but also the mobility of each DRG within the distribution. Thus such an approach helps identify certain inter-DRG allocative patterns which might be induced by the continuing PPS regime. The empirical distributions are estimated using the "stochastic kernel approach" based on Markov Chain theory. A stochastic kernel can be defined as a complete description of transitions from state 'i' to state 'j' in an empirical distribution. For example, the stochastic kernel related to an empirical distribution of average LOS in each DRG will help answer the following question: What is the probability that proportion of LOS in a particular group of DRGs will increase, decrease or remain same in the next two years? The paper uses monthly Victorian patient data (around one million patient episodes each year) with a time span of eight years (1998-99 to 2005-06).

The empirical analysis is done separately for inlier and outlier episodes. The main conclusions are : For inlier episodes, over a 2 year transition, the DRGs with high quantile shares of LOS are likely to have their shares reduced (transition of LOS shares from high to low), DRGs with middle quantile shares of LOS will likely to have their shares unchanged (persistence of shares), DRGs with low shares of LOS will likely to have their shares further reduced (transition of shares from low to lower). Thus the distribution of LOS shares for inlier episodes shows emergence of three peaks, most prominent being in the middle of distribution comprising of maximum number of DRGs. The empirical analysis further tests the hypothesis that change in relative prices of DRGs explain the stratification of inlier shares. This is done by using a conditional approach where stochastic kernels are reestimated using share of inliers weighted by relative price of DRGs. The results reveal that DRG prices are one of the factors explaining resource allocation decisions across DRGs. For

[3]It should be noted that *ex-ante* hospitals would like to specialize in the "lucrative" DRG treatment (Rauner et al., 2003) but *ex-post* in a continuing PPS regime, even a specialist hospital will have an incentive to redistribute its resources in response to temporal changes in relative DRG weights.

high outlier episodes, over a 2 year transition, the cross section LOS distribution of DRGs converges to zero. This indicates that in the current case-mix funding regime, hospitals are less likely to have high outlier episodes.

The empirical evidence for both inlier and outlier episodes is consistent with the behaviour of hospitals suggested by the theoretical models in extant literature. For example, transition of LOS shares from low to lower values could be mainly because of reduction in the number of patients in these DRGs. Given almost constant patient profile in last 8 years, this reduction in inpatient numbers could be result of change in the intensity of treatment for patients with low average LOS or a potential selection for patients with high average LOS. Similarly, the likelihood of reduction in the high outlier episodes indicates existence of potential selection effect even in a continuing case-mix regime. Thus the empirical methodology used in this paper sheds further insight into the resource allocation across DRGs, which was not possible by using traditional econometric methods. The rest of the paper is organized as follows: Section 2 gives a background on the case-based payment system in Victoria. Section 3 proposes an analytic framework to motivate empirical analysis. Section 4 discusses the data and methodology. The results are discussed in Section 5. Section 6 concludes.

2 Case-based payment system for inpatients in Victoria

The case-based payment system also known as case-mix funding was introduced in Victorian public hospitals in 1993. Prior to this public hospitals were funded on a global budget basis or "historical plus" system. Under a global budget basis each hospital annually negotiated its budget with the Health Department. The budget was adjusted upwards to account for inflation and new programs in the hospital and then slightly adjusted downwards in anticipation of productivity savings. The output was measured in bed-days (number of inpatient hospital days) and number of separations (number of inpatient discharges). Under such a funding regime, distinction between hospitals on the basis of complexity of patients treated was limited. After the introduction of case-mix funding the hospitals were funded on the basis of volume adjusted for complexity.

The main objective of introducing the case-mix funding in Victoria was to achieve significant reductions in health expenditures while maintaining service outputs. This was implemented by the policy of paying on the basis of products and not capacity of hospitals. In a case-mix funding regime, the admitted patients output is counted by coding hospital separations into DRGs. The DRGs are determined on the basis of the diagnosis codes for patient episodes. These codes are based on ICD 10 classification and hospitals can enter up to 24 diagnosis codes for each patient episode. Each DRG is assigned a weight based on its relative resource consumption. Each patient separation is multiplied by the corresponding DRG weight and this weighted throughput is used for counting the output for funding purposes. In addition this formula is further adjusted for unusually long stay and short stay patients. Such patients are determined by setting low and high trim points for each DRG.

In Victoria, the trim points are set at one-third and three times the average LOS for that DRG. Patients with LOS between the trim points are called inliers and patients with LOS above and below the trim points are called high and low outliers respectively. Low outlier cases receive a fraction of inlier case weight. On the other hand, hospitals receive some additional weight for high outliers for *each day* above the high trim point. It should be noted that the daily additional weight is related to the inlier weight and the average length of stay but the relationship varies for different DRGs and is subject to the ceiling and flooring restrictions. Such an adjustment enables each adjusted outlier separation to be expressed in terms of equivalent inlier weights and is termed a Weighted Inlier Equivalent Separation (WIES). Thus WIES is the unit of counting admitted patient throughput under the case-mix formula.

In each funding round the health department sets up a price per unit of WIES using a “top down” approach in which prices are determined on the basis of amount allocated to the health budget rather than on the basis of a benchmark cost. Thus the case-mix formula is not a price setting mechanism and does not reflect actual costs of treatment. The DRG cost weights are determined from a series of specific cost weight studies commissioned by the health department. These studies are undertaken mostly by the large/metropolitan hospitals which have resources to undertake such sophisticated costing exercise[4]. Though the quality of cost weight studies is increasing, the systems ability to fine tune the weights has been questioned because of high volatility of DRG cost weights. The volatility in DRG cost weights between the funding rounds combined with temporal changes in the price per unit of WIES may transform a specific DRG from profitable ("lucrative") to loss-making ("non-lucrative"). This might send price signals to the hospital to reduce number of procedures in that DRG.

The funding regime of Victorian hospitals is not purely based on case-mix and in addition to WIES funding, hospitals also get additional funding in the form of fixed overhead costs, specified grants for teaching and research, performance and quality incentives and bonus funding for hospital demand management strategies. The health department encourages efficiency by setting WIES targets for each hospital and a public throughput above 2% of this target is penalised by reductions in the bonuses payable to the hospital. In addition to WIES targets hospitals also face targets under the Hospital Access Program (HAP) relating to waiting times for emergency services, critical care and elective surgery. In the short term, under the pressure of meeting multiple targets hospitals face a real risk of bearing an operating deficit. Thus, in order to minimize such deficits, hospitals may try to maximise their revenue by reallocating resources within DRGs (particularly related to elective patients). Thus in the Victorian 'fixed and variable' case-mix funding regime hospitals' behaviour reflects responses to fixed costs (infrastructure, salaries etc.), variable costs (WIES) and marginal cost (per diem expenses for high outliers) components. The payment system is not fully prospective and can be at best called a mixed payment system with most of the payment being prospective.

3 Analytic Framework

As discussed in the previous section, in a continuing PPS regime, funding is at a DRG level and all hospitals or hospital groups get the same amount for treating patients from a

[4]Therefore only large/metropolitan hospitals are effectively capable of reallocating the resources across DRGs, in response to changes in cost weights. Thus only such hospitals are used for empirical analysis in the present paper. These hospitals account for 85-90% percent of hospital separations in Victoria.

particular DRG. The main objective of this paper is to analyse the distribution dynamics of resource allocation decisions across DRGs in a PPS. Thus the analysis is done at DRG level for the hospital sector as a whole. This is mainly because, specifically in our case, where we focus on elective surgeries, a hospital level study may give misleading results regarding potential patient selection. For example, unobserved patient choice for elective treatment may be responsible for changes in DRGs share of LOS across hospitals which could be picked up as selection effect in a hospital level analysis. On the other hand, if a particular DRGs' share of resource use changes significantly at the hospital sector level, it indicates a potential selection effect or change in treatment intensity in response to a relative price change of that DRG[5]. A funding body will also be interested in the patterns of resource allocation within DRGs at the hospital sector level rather than at the individual hospital level. A potential selection effect at hospital sector level indicates that some patients might miss out on hospital treatment altogether, which is a critical policy issue in terms of adverse health outcomes of the population. The analysis of hospital level selection is certainly an avenue for research but more appropriate for studies with goals other than those here.

This section formally quantifies the effect of the reimbursement system on the average resource use at a hospital sectoral level. This is done by extending the hospital level framework suggested by Ellis and McGuire (1996) to DRG level. The framework decomposes the impact of relative price changes of DRGs on average resource use for the hospital sector. Let us assume that a patient seeks elective treatment for DRG i. In a PPS the patient might be subjected to an admittance criteria based on the relative price of DRG i: $A_i(p_i)$ where A_i is the admittance criteria and $(\mathbf{p})$ is the relative price vector $\mathbf{p}$. For example, such an admittance criteria might be based on a decision rule where patients who are perceived to be high outliers will be avoided. Similarly, a patient might be subjected to different treatment intensity $(T_i(p_i))$ based on the reimbursement system. For example, if relative price of DRG i is perceived to be low then the patient might be discharged *"quicker and sicker"* from the hospital. Thus the admittance criteria (A), treatment intensity (T) and the severity of patients (V) jointly determine the number of patients treated in DRG

[5]It should be noted that effect of change in patient profile on resource use will be negligible as patient profile for elective DRGs is almost constant in Victoria during the 8 year period considered for our analysis.

i and their corresponding LOS. Formally:

$$N_i = N_i(A_i(p_i), T_i(p_i)) \tag{1}$$

$$V_i = V_i(A_i(p_i), T_i(p_i)) \tag{2}$$

$$LOS_i = L_i(V_i(p_i), T_i(p_i)) \tag{3}$$

where

N_i = Number of patients treated in DRG i

V_i = Severity of patients treated in DRG i

LOS_i = Length of Stay for DRG i

Denoting DRG i's share of discharges as S_i the LOS across all DRGs is:

$$LOS = \sum_i S_i \;\; LOS_i \tag{4}$$

Given Eqns (1), (2) and (3) total effect of reimbursement system on resource use can be decomposed into three components:

$$\frac{dLOS}{dp} = \left[\sum_i \; S_i \frac{\partial LOS}{\partial T_i}\frac{\partial T_i}{\partial p_i}\right] + \left[\sum_i \; S_i \frac{\partial LOS}{\partial V_i}\frac{\partial V_i}{\partial p_i}\right] + \left[\sum_i \; LOS_i \frac{\partial S_i}{\partial p_i}\right] \tag{5}$$

The first term is the moral hazard effect, the second term is the selection effect and the third term is what we define as the redistribution effect. This paper focusses on quantifying the redistribution effect by using the non-parametric approach of stochastic kernels. In particular we focus on the impact of relative price changes on the share of resource use (S_i) for a particular DRG. As evident from first two terms of Eq. (5), moral hazard effect and selection effect are also functions of S_i and thus an evidence of change in shares in response to change in relative prices could also indicate potential selection effect at hospital sector level.

4 Empirical Methodology

In order to test for the behavioural response of hospital sector towards temporal changes in relative weights of DRGs, the empirical framework focusses on the cross-DRG distribution dynamics of DRG's share of inlier and outlier LOS relative to total LOS. As an illustration, consider Figure 1 where the vertical axis indexes share of inliers in each DRG and horizontal axis, time. Figure 1 records the densities corresponding to cross-DRG inlier distributions, over two time periods. Figure 1 represents a hypothetical scenario where in period t most DRGs have medium levels of inlier shares and there are very few DRGs with very high or very low inlier shares.

As discussed earlier, in a PPS the relative weights of DRGs change over each funding round and thus the distribution of inliers across DRGs is likely to fluctuate. For example as illustrated in Figure 1, the inlier distribution for the same pool of DRGs changes shape in period $t+s$ and shows a patterns where share of inliers for some DRGs have increased (for example as in DRG 1), decreased (for example as in DRG 3) or remained almost the same (for example as in DRG 2). In addition the period $t+s$ distribution also reveals a pattern of clustering where DRGs with very high inlier shares have clustered together, DRGs with medium inlier shares have clustered together and DRGs with very low inlier shares have clustered together.

Such an emerging pattern of clustering with multiple peaks is in contrast to the distribution in period t and is termed as *stratification*. Since the underlying population in our analysis are DRGs such a behaviour of stratification might result from selection effect, moral hazard, practice style effect or a combination of all three.

—Insert Figure 1 about here—

The empirical analysis in this paper explores such patterns by analysing the *intradistribution dynamics* of the cross-DRG distributions, using actual inpatient data. For example, Figure 1 indicates towards three types of intradistributional dynamics: i) Persistence: Some DRGs in period $t+s$ have almost the same inlier ratio as in period t (e.g. DRG 2); ii) Churning or Mobility: Some DRGs which have a high ratio of inliers in period $t+s$ had a lower ratio of inliers in period t (e.g. DRG 1) and some DRGs which have a lower ratio of inliers in period $t+s$ had a higher ratio of outliers in period t (e.g. DRG; 3) iii) Clustering or stratification: DRGs have clustered into three distinct categories which has led to some DRGs which had similar share in period t to separate from each other and be part of different clusters in period $t+s$.

Thus Figure 1 represents a evolving pattern of inlier distributions across two time periods with mobility and stratification of the distribution happening simultaneously. The econometric framework in the present paper intends to capture such distributional dynamics. In addition, the empirical model will also project such distributional dynamics in future using the observed data. The econometrics of analysing the distribution dynamics directly was introduced in the economic growth literature by Quah (1997, 1990). Quah argued that the extant empirical techniques were incapable of capturing the intradistribution dynamics. For example comparing the mean and variances of the cross sectional distributions of DRGs over time will not shed any light on the stratification or mobility of the distribution.

Similarly, comparison of time series behaviour of outlier shares in each DRG or sub-groups of DRG will also be uninformative on distribution dynamics. Even the more sophisticated techniques of cross section and panel data regressions capture the behaviour at the conditional mean and will not be useful for analysing dynamic behaviour of distributions. The impact of a continuing PPS regime on the allocation of resources across DRGs can be best captured by analysing the mobility or churning of DRG distributions. Quah (1997) suggests the use of stochastic kernels for such a analysis, which are discussed next.

4.1 Stochastic Kernel

A stochastic kernel is a mapping which quantifies how distributions evolve over time. The distribution dynamics methodology (Quah, 1997) assumes that the density distribution ϕ_{t+1} for the shares evolves according to a Markov process:

$$\phi_{t+n} = M \cdot \phi_t \tag{6}$$

where M is an operator mapping the transition between the share distribution existing in time t to the share distribution in time $t+n$. Thus stochastic kernel is a continuous time variant of a discrete transition probability matrix (TPM). A TPM is an alternative way of quantifying distribution dynamics where, for example, outlier shares of DRGs are categorized in distinct discrete cells and then the observed transitions out of and into these discrete cell are counted. However, Quah (1997) and Chung (1967) argue that such a discretisation of a continuous variable (share of inliers and outliers in our case) can distort the distribution dynamics and lead to misleading results. Thus any categorization of outlier shares into specific ranges will be arbitrary and such an arbitrariness means that setting out different ranges of share of outliers might give different conclusions about the actual projection of distribution in the future.

Quah (1997) further argues that instead of discretisation the number of distinct cells in a TPM should be allowed to tend to infinity and then to the continuum. The corresponding TPM with a continuum of rows and columns is termed as stochastic kernel. Thus a stochastic kernel can be formally defined as[6]:

Definition 1 ***Stochastic Kernel*** *Let* μ *and* ν *be elements of* $\mathbf{B}$ *that are probability measures on (R,* $\Re$*). A stochastic kernel relating* μ *and* ν *is a mapping* $M_{(\mu,\nu)}$*: (R,* $\Re$*)* $\rightarrow$ *[0,1] satisfying:*

(i) $\forall$ *S in R, the restriction* $M_{(\mu,\nu)}(S,.)$ *is a probability measure;*

(ii) $\forall$ *A in* $\Re$*, the restriction* $M_{(\mu,\nu)}(.,A)$ *is* $\Re$ *measurable;*

(iii) $\forall$ *A in* $\Re$*, we have* $\mu(A) = \int M_{(\mu,\nu)}(S,A)d\nu(S)\ M_{(\mu,\nu)}(.,A)$.

where:

$(R, \Re)$ is the underlying state space with R being the real line and $\Re$ collection of its Borel sets.

$\mathbf{B}(R,\Re)$ denotes the Banach space of bounded finitely-additive set functions on the measurable space $(R, \Re)$ endowed with total variation norm:

$\forall\mu$ in $\mathbf{B}(R,\Re)$: $\quad |\mu| = \sup \sum_j |\mu(A_j)|$

where the supremum in this definition is taken over all A_j: j = 1,2,.....n finite measurable partitions of R.

[6] For the technical derivation of stochastic kernel interested readers can refer to Section 4 in Quah (1997).

The main concept of stochastic kernel is defined by condition (iii). Taking initial period as t, for a given LOS share S there is a fraction $d\nu(S)$ of DRGs with shares close to S. In period $t+n$ part of DRGs contained in $d\nu(S)$ will move to a subset $A \subseteq R$. Normalising this fraction of DRGs by the total number of DRGs, we have the stochastic kernel given by $M_{(\mu,\nu)}(S, A)d\nu(S)$.

4.2 Estimating Stochastic Kernels

Stochastic kernels are generated by applying explicit laws of motion to the cross section distributions. For estimation purposes, stochastic kernel can be written as (Arbia et al., 2005):

$$\phi_{t+n}(S) = \int_0^\infty f_n(S|S')\phi_t(S)dS \tag{7}$$

where S is the share in period $t+n$ and S' is the share in period t. $f_n(S|S')$ is the *conditional* density which describes the probability that a DRG moves to a specific state of share, given the share in period t. Thus a stochastic kernel can be expressed as a conditional density and its estimator can be derived from the estimation of conditional density. A nonparametric estimator for the conditional density as proposed by Rosenblatt (1956) is given by:

$$\hat{f}_n(S|S') = \frac{\hat{g}_n(S', S)}{\hat{h}_n(S')} \tag{8}$$

where the estimator for the joint density $\hat{g}_n(S', S)$ is given by:

$$\hat{g}_n(S', S) = \frac{1}{Jab}\sum_{j=1}^{J} K\left(\frac{||S' - S'_j||}{a}\right)\left(\frac{||S - S_j||}{b}\right) \tag{9}$$

and the estimator for the marginal density $\hat{h}_n(S')$ is given by:

$$\hat{h}_n(S') = \frac{1}{Ja}\sum_{j=1}^{J} K\left(\frac{||S' - S'_j||}{a}\right) \tag{10}$$

where a and b are bandwidth parameters controlling the smoothness of fit, K is the chosen kernel function and $||S' - S'_j||$ and $||S - S_j||$ are the Euclidian metrics. Substituting Eqs

(9) and (10) in (8) the conditional density estimator can be rewritten as:

$$\hat{f}_n(S|S') = \frac{1}{b}\sum_{j=1}^{J} w_i(S')K\left(\frac{||S - S_j||}{b}\right)$$

where

$$w_i(S') = K\left(\frac{||S' - S'_j||}{a}\right) / \sum_{j=1}^{J} K\left(\frac{||S' - S'_j||}{a}\right)$$

The above kernel estimator is the Nadaraya-Watson kernel regression estimator. It shows that a conditional density can be obtained by the sum of J kernel functions in S space weighted by the $w_i(S')$ in S' space. In order to estimate the conditional density the issue of optimal bandwidth and kernel choice is crucial (Pagan and Ullah, 1999). Quah (2004) reports a measure of relative efficiency based on the cross validation criteria of minimum integrated least square error, where the bandwidth is permitted to vary with the kernel K using the method suggested by Silverman (1986). According to this criterion Epanechnikov kernel turns out to be optimal but the other kernels also achieve efficiencies close to it (Quah, 2004). We use Epanechnikov for our empirical analysis. The bandwidth or the smoothing parameter is calculated using the methodology suggested by (Silverman, 1986). The choice of bandwidth is not arbitrary and is data dependent and thus the stochastic kernel estimation is robust to bandwidth selection.

The assumptions of Markov process underlying the stochastic kernel estimation used in our analysis are noteworthy. We assume that the transition probability of DRG share from value i to j, say in response to a unit change in relative price of DRG, is constant over time. In other words, the behavioral response of hospital sector to a continuing PPS remains consistent over time. This is a plausible assumption as there is no significant structural shift in PPS in Victoria in last 8 years considered for our analysis. Such an assumption of time homogeneity is common to Markov models used in economics and health economics applications even for time spans longer than that used here (For example see Quah (1997); Norton (1992); Craig and Sendi (2002)). In addition, by definition Markov property holds which states that given the entire past history, the present state depends only on the penultimate state. Since the empirical analysis is done at a DRG level the data is aggregated over all hospitals. Such an aggregation could lead to a bias at hospital sector level. Thus the empirical analysis is restricted to major teaching and suburban hospitals to ensure homogeneity among hospitals. These hospitals account for 85-90% of elective surgical episodes in Victoria. In fact for some so called tertiary DRGs all the patients are treated in these hospitals. These hospitals belong to same payment group under the case-mix funding regime, are research active and have same technological inputs for treating patients.

The stochastic kernel technique is best suited for our analysis as: i) it allows us to trace the distribution dynamics of DRGs within a distribution which is not possible to estimate using a parametric method ii) it can be applied in the settings of patient level analysis where detailed data is not available due to confidential reasons and iii) it allows for conditioning of covariates on distribution to analyse the impact of variables on the distribution dynamics which helps answer interesting policy questions. For example, in this paper we analyse the impact of relative price of DRGs on distribution dynamics and conclude that for inlier episodes relative prices in DRGs are one of the determinants in resource allocation across DRGs. The results obtained by applying the stochastic kernel mapping on the current distribution can be displayed in a three dimensional diagram or a two-dimensional contour map. The empirical methodology in this paper applies stochastic kernel mapping to quantify the evolution of distribution of DRG's shares of outliers and inliers by using inpatient data in Victorian hospitals.

4.3 Data

The empirical study uses Australian patient level Victorian Admitted Episodes Dataset (VAED) with a time span of eight years (1998-99 to 2005-06). VAED data is the most appropriate for the analysis as this dataset is used for health services planning, policy formulation and case-mix funding purposes. The dataset consists of over one million patient episodes per year with detailed information on length of stay, diagnosis, patient origin etc. As discussed earlier only large hospitals have the resources to undertake sophisticated case-mix costing exercises and thus mostly these hospitals will respond to change in DRG cost weights. Thus our analysis is restricted to large teaching and suburban hospitals. The data is further refined by removing emergency cases.

The patients' diagnosis in the data is coded by Australian Refined Diagnosis Related Group (ARDRG) which are slight modification of standard DRG codes based on ICD-10 AM classification. The DRG code definitions reported in VAED are adjusted for DRG reclassification and are consistent throughout the eight years. The variable "w12_ifs" classifies each patient episode into a low outlier (coded as "L"), inlier (coded as "I") or high outlier ("H"). Outlier patient episodes are determined by setting low and high trim points for each DRG. In Victoria, the trim points are set at one-third and three times the average LOS for that DRG and this benchmark of determining outliers is consistent over eight years of observed data. The empirical analysis is done at DRG level.

4.4 Variables

The allocation of resources across DRGs is captured by two types of DRG specific variables: i) Share: LOS of outliers/inliers in a particular DRG *relative* to LOS of outliers/inliers in all DRGs; ii) Proportion: LOS of outliers/inliers in a particular DRG *relative* to total LOS (including both outlier and inlier episodes) in all DRGs. Thus for high outliers, the share of each DRG is calculated by dividing the total LOS of high outliers in that DRG to total LOS of high outliers across all DRGs. Thus for DRG i the share of outlier is:

$$Sh_i^{HO} = \frac{LOS_i^{HO}}{\sum_{i=1}^{N} LOS_i^{HO}}$$

where LOS_i^{HO} denotes total LOS in high outlier episodes of DRG i.

Thus this share represents the LOS distribution of high outlier episodes in a particular DRG relative to LOS distribution of high outlier episodes in all DRGs. Similarly the share of inliers (Sh_i^I) can be defined as:

$$Sh_i^I = \frac{LOS_i^I}{\sum_{i=1}^{N} LOS_i^I}$$

where LOS_i^I denotes total LOS in inlier episodes of DRG i. The proportions for high outlier episodes Pr_i^{HO} and inlier episodes Pr_i^I for a particular DRG are defined as:

$$Pr_i^{HO} = \frac{LOS_i^{HO}}{\sum_{i=1}^{N} LOS_i}$$

where LOS_i^{HO} denotes total LOS in high outlier episodes of DRG i and LOS_i total LOS (including inliers and outliers) of DRG i.

$$Pr_i^I = \frac{LOS_i^I}{\sum_{i=1}^{N} LOS_i}$$

LOS_i^I denotes total LOS in inlier episodes of DRG i and LOS_i total LOS (including inliers and outliers) of DRG i.

The main advantage of using proportions and shares is that they neutralize the effect of overall reduction in LOS after the introduction of case-mix funding regime. It is to be noted that the LOS has on an average decreased by 10 percent after the introduction of case-mix funding (AIHW, 2005). The use of proportions and shares in empirical analysis ensures that the patterns of resource allocation across DRGs capture only the *redistribution* of reduction in LOS. In addition, as evident from Eq (5) theoretically, shares are crucial in determining impact of reimbursement system on resource use.

The extant studies on effect of PPS have mainly focussed on its impact on average LOS. The empirical analysis in the present paper takes a step further and sheds light on the distribution of LOS changes across DRGs. The advantage of using shares and proportions is that it will shade more light on how these changes in average LOS have been distributed across DRGs. The empirical analysis uses a balanced panel of 177 DRGs over 96 months. The summary statistics of the panel data are presented in Table 1.

—Insert Table 1 about here—

The empirical methodology involves stochastic kernel mapping of above defined shares and proportions. Such a mapping will reveal the direct distribution dynamics of outlier and inlier episodes in a continuing PPS. In addition, based on the actual observed data, a projection of distribution is made for a horizon of 24 months.

5 Results

The stochastic kernel mapping is done separately for inlier patient episodes and high outlier patient episodes. In addition, the stochastic kernel for inlier shares is restimated by conditioning it on the relative price of DRGs. This is done in order to test if relative prices explain the changes in the distribution dynamics of resource allocation across DRGs.

5.1 Inliers

The upper half of Figure 2 shows the stochastic kernel and corresponding contour plots[7] for 24-month transitions in the share of inliers data. The choice of a 24 month transition is only for convenience and clarity as transitions probabilities across different states of inlier shares are independent of time (time homogeneity assumption of the Markov Process). The stochastic kernel could be traced by picking any point on the axis marked 'Period t' and extending it parallel to the axis marked 'Period $t+24$'. Thus the stochastic kernel is a probability density function and the projection traced out 24 months ahead is nonnegative and integrates to unity. The projection is analogous to the row of a discrete transition probability matrix where probabilities in different states sum up to 1. Thus stochastic kernel mapping can be used to trace the share of inliers over a 24 month period.

Figure 2 shows how the cross sectional distribution at time t evolves into that at $t + 24$. The distribution will show the behaviour of persistence if most of the graph in Figure 2 was concentrated along the 45-degree diagonal. This would mean that inlier shares in the distribution remain where they began. However, if say share of inliers in the DRGs change drastically i.e. DRGs with a high share of inliers in period t become DRGs with a low share of inliers in period $t + 24$ (high to low transition) and DRGs with low share of inliers become those with a high share of inliers in period $t + 24$ (low to high transition), the stochastic kernel mapping will rotate 90 degrees counter-clockwise from that 45-degree diagonal.

Figure 2 shows a multiple peaks feature in the distribution of inlier shares. The shares of inliers have stratified and the stochastic kernel rises towards three local maxima. This is reflected by an emergence of three peaks which is clear from the corresponding contour plot of the kernel.

—Insert Figure 2 about here—

[7] The econometric analysis is done using the tsrf shell provided by Danny Quah.

The lines on the contour plot connect points at the same height on the three-dimensional kernel. The contour plot further reveals the peak at the lower quantile of shares (peak 1) shifts left of the 45 degree line whereas the peaks on the middle quantile (peak 2) and higher quantile (peak 3) remain on the 45 degree line. The emergence of peak 2 is a significant finding. Its main interpretation is that over a 24 month horizon the DRGs with middle quantile inlier shares will increase. Most of the portion of probability mass remains clustered around the main diagonal. However, the two dips on the principal ridge of the distribution (across the 45 degree line) in Figure 2 indicate that portions of the cross section do transit from low to middle level, and high to middle level, thereby contributing to formation of peak 2. In addition the middle portion of the cross section shows a behaviour of persistence over a 24 month time horizon. Peak 1 has a lower number of DRGs compared to peak 2 and is located slightly to the left of the 45 degree line. This indicates that DRGs with lower shares of inliers in period 't' will have their shares decreased in period 't+24'. Peak 3 has the least number of DRGs which means that over a 24 month horizon numbers of DRGs with inlier shares in the higher quantile range in period 't' will decrease. The intensity of the graph (marked by darker shades) reveals that variation of shares in DRGs around peak 1 is lowest and around peak 3 is highest.

As discussed earlier, in a case-mix funding regime, the hospitals get a lumpsum payment (based on DRG weights) for inlier episodes in each DRG. Thus the marginal benefit to hospitals for keeping the inlier patient for an extra day is zero whereas the marginal cost is positive. Hence the hospitals have an incentive to keep the LOS of inlier episode to a minimum by choosing less severe patients (selection effect) or changing the intensity of treatment provided to patients (moral hazard effect) or by specializing. The empirical evidence derived from the evolving distribution of share of inliers discussed above (especially the transition of DRGs from high shares to low shares) indicates that either one or combination of these effects might be contributing towards hospital behaviour. For example, there is tendency that over a 24 month horizon the DRGs with a higher quantile of inlier LOS shares (in period 't') (peak 3) will decrease. The transition from low shares to high shares (occurring for some DRGs between peak 1 and 2, and peak 2 and 3) indicates that some DRGs will increase their share of LOS in inlier episodes. This means that hospitals will redistribute resources for elective surgeries in a way that the share of LOS increases for some DRGs. Such a behaviour of Victorian hospitals could be the result of: i) the government's policy of targetting select DRGs to reduce waiting times for elective surgery by providing additional targetted funding; ii) Hospital's policies of maximizing revenue from government funding (these DRGs might be profit making or "lucrative" for hospitals).

The slight anti clockwise rotation of peak 1 indicates that DRGs with a lower share of inliers in period 't' will have their shares further decreased in period 't+24'. Transition of LOS shares from low to lower values could be mainly because of reduction in the number of patients in these DRGs. Given almost constant patient profile in last 8 years, this reduction in inpatient numbers could be result of change in the intensity of treatment for patients, i.e. the patients in DRGs which have low average LOS might be treated as same day patients and such a behaviour might be contributing towards a consistent annual increase of 5 percent in same day separations in Victorian hospitals. Although the funding for same day patients is lower than those of inliers, hospitals save on the fixed costs associated with an inlier multi day admission and hence could find a sameday episode relatively profitable. On the other hand the reduction in inlier shares from 'low to lower' for patients in DRGs with higher average LOS indicates potential selection effect where these patients are left out of elective hospital treatment altogether. The intradistribution dynamics of the proportion of inliers is presented in lower half of Figure 2. The proportion of inliers show similar trends as the share of inliers.

Thus the results from intradistribution dynamics of LOS share for inliers suggest that overtaking and persistence is occurring simultaneously in the inlier distribution and most of the trends in evolution of distribution are consistent with the possible theoretical explanations of impact of case-mix funding on the supply of hospital care discussed in the extant literature. We next focus on the factors which explain such distribution dynamics of inlier shares. Ideally, detailed data on costing of each patient episode can shed light on profitability of treating patients in a particular DRG which can be subsequently used to check if resources are being transferred from non profitable to profitable DRGs. Unfortunately, such data is not commonly available for research purposes because of confidentiality issues. Therefore, we use relative prices of DRGs as a proxy to test if these are responsible for stratification of inlier shares. One main contribution of this study is that the proposed methodology outlined in this paper provides a framework to analyse the impact of covariates on distribution dynamics by conditioning the stochastic kernel. The impact of relative prices of DRGs on the distribution of inlier shares is discussed next.

5.1.1 Impact of relative prices of DRGs

The evidence of stratification of inlier shares in the above section was obtained by using unconditional distribution dynamics. The obvious next step would be to do a conditional analysis which sheds more light on the underlying factors that *explain* the distributional dynamics of inliers. In particular we want to condition on the relative prices of DRGs as these are argued to be a crucial determinant of resource allocation across DRGs. The data on relative prices of DRGs is taken from various issues of Victoria - Public Hospitals Policy and Funding Guidelines published by the Department of Health Victoria. These guidelines report relative cost weights for each DRG which are used to calculate the weighted inlier equivalent separation (WIES) for each inlier episode. For example an inlier episode in DRG A with relative cost weight of 0.5 will have WIES of 0.5 and an inlier episode in DRG B with relative cost weight of 1.5 will have WIES of 1.5. The funding body decides a dollar value of unit WIES in each funding round. The product of this dollar value to WIES is the relative price of DRG. Thus if hospital treats exactly same number of patients with same number of LOS in DRG A and B, it will get more funding for patients in DRG B as they have higher WIES relative to DRG A. In order to condition for relative prices of DRGs we weight the DRG shares and proportions used in unconditional analysis by corresponding WIES. The conditional analysis uses 75 DRGs which are subset of DRGs used in unconditional analysis. The sample of DRGs was restricted to 75 because of lack of consistent data on cost weights for other DRGs.

—Insert Figure 3 about here—

The stochastic kernel and corresponding contour maps for weighted shares are reported in Figure 3. The unconditional plots of stochastic kernels and corresponding contour map for same 75 DRGs are also reported to enable a direct comparison between conditional and unconditional distribution dynamics. The unconditional plots again confirm the evidence of stratification in inlier shares as shown by the emergence of three peaks out of which two peaks are prominent. The stochastic kernel on the weighted shares will describe how relative prices of DRGs will alter the cross sectional distribution of shares. Thus, to test our hypothesis that change in relative prices of DRGs is resulting in the stratification of inlier shares, we need to observe if the stochastic kernel transforming the unconditional distribution to conditional one removes the stratification or polarization of inlier shares. The conditioned stochastic kernel reported in Figure 3 confirms that the stratification is removed after the inlier shares are weighted by relative DRG prices. Thus relative prices are one of the determinants of resource allocation across DRGs. The results for proportions show similar trend and are skipped here.

5.2 High Outliers

The stochastic kernel mapping and corresponding contour plot for high outlier shares are presented in upper half of Figure 4. The graph reveals the stochastic kernel is not positive for all shares and hence there is no one to one correspondence in probabilities for some share points. The overall trend shows that over a 24 month period, most of the DRGs with a positive share of high outliers in period ‘t’ will have very low or zero share of high outliers in period ‘t+24’. Though there are some peaks on the contour plot which are randomly distributed over the distribution, most of the distribution is concentrated around the 0-value of the period ‘t+24’ axis– extending parallel to the period ‘t’ axis. This indicates that over a 24 month horizon the cross sectional distribution of DRGs will converge to zero. The main conclusion from this result is that the case-mix funding regime is inducing the hospitals to reduce high outlier episodes in elective surgery patients. This might be happening in the form of potential selection effect (hospitals choose not to treat patients which are more likely to have high outlier episodes) or due to a *“quicker and sicker”* phenomenon where hospitals discharge patients before their episode becomes a high outlier. The mapping using proportions of high outlier episodes and the corresponding contour maps are presented in lower half of Figure 4. The intradistribution dynamics of proportions is similar to those of shares.

—Insert Figure 4 about here—

As discussed earlier, a high outlier episode is funded on a per diem basis once the patients

LOS is three times more than the average LOS. However, the per diem payment rate in Victoria is determined by the fraction of the inlier weight and does not reflect the actual cost of treating a high outlier patient. Thus, even though the marginal revenue of keeping a patient is positive in a high outlier case, it might be below the marginal cost and hospitals might prefer to under service such patients. Unfortunately, it is not possible to do a conditional analysis on high outlier episodes at this stage because of lack of availability of data on some variables required to calculate high outlier DRG cost weights.

6 Conclusions

This paper has analysed the patterns of shares and proportions of high outlier and inlier episodes across DRGs from the perspective of distribution dynamics. The empirical analysis has captured a behaviour of stratification in shares of inlier episodes and unipolarization in the case of high outliers. For inlier episodes, over a 2 year transition, the DRGs with high quantile shares of LOS are likely to have their shares reduced (transition of LOS shares from high to low), DRGs with middle quantile shares of LOS will likely to have their shares unchanged (persistence of shares), DRGs with low shares of LOS will likely to have their shares further reduced (transition of shares from low to lower). Thus the distribution of LOS shares for inlier episodes shows emergence of three peaks, most prominent being in the middle of the distribution comprising of the maximum number of DRGs. The conditional analysis concludes that change in relative prices in DRGs is one of the factors affecting resource allocation across DRGs. For high outlier episodes, over a 2 year transition, the cross section LOS distribution of DRGs converges to zero. This indicates that in the current case-mix funding regime, hospitals may have no incentive to treat high outlier patients.

The empirical evidence for both inlier and outlier episodes is consistent with the behaviour of hospitals suggested by the theoretical models in the extant literature. For example, transition of LOS shares from low to lower values indicates either a change in intensity of treatment for DRGs with low average LOS or potential selection for DRGs with high average LOS. Specifically, patients in DRGs with a very low share of inlier and low average LOS might be treated as same day patients and such a behaviour might be contributing towards a consistent annual increase of 5 percent in same day separations in Victorian hospitals and so may indicate cost shifting by hospitals or technological changes. Similarly, the likelihood of reduction in high outlier episodes and inlier episodes with high average LOS indicates existence of potential selection effect even in a continuing case-mix regime. This may be because, even though hospitals get extra per diem payment for the high outlier episodes, it is determined by the inlier weights and not the actual cost of treatment. Thus in spite of a positive marginal revenue in treating a high outlier patient, the hospitals might still be making losses. Thus the empirical methodology used in this paper sheds further insights into the resource allocation of hospitals across DRGs, which is not possible using traditional econometric methods.

The main policy implication from the empirical analysis is that allocation of resources across DRGs is responsive to changes in relative prices of DRGs. The evidence of potential selection effect especially among high cost patients also raises an interesting policy issue. Many of the high cost patients in elective surgery may come from a lower socioeconomic background (Agabiti et al., 2007). These groups will face adverse health outcomes as a result of selection effects. Selection can also have an adverse impact on waiting times for elective surgery. Although current government policies such as introduction of per diem payment for high outlier episodes, putting caps on waiting times and paying extra for Aboriginal patients might have reduced the incentives to select, our results find strong evidence of potential selection especially for high cost patients. Thus one policy suggestion would be to further reduce the extent of prospectivity in payment for high cost patients and increase monitoring of hospitals.

The results from present study could be useful to understand the trends in hospital efficiency in Victorian hospitals. As Jacobs et al. (2006) argue stand alone efficiency analysis treats a DMU as a black box and explains little as to why a particular level of efficiency is observed. The main inferences from our study could be used as additional information by policy makers to understand the underlying factors that could be causing changes in efficiency levels.

The methodological contribution of the present paper is that it has outlined an empirical methodology to identify patterns of inter-DRG resource allocation in a continuing PPS.

The application of stochastic kernel (a non parametric approach) to capture evolution of the whole distribution has an advantage over standard regression methods which only provide a picture of the behaviour of conditional mean. Further, the panel data econometric methods control for and thus absorb heterogeneity into “individual effects” which would not allow us to explain differences across DRGs.

The next step could be to explore additional factors which could explain distributional patterns of inter-DRG resource allocation. For example part of the potential selection effect could be caused by recent government policies to improve quality of care in hospitals. Similarly, part of the change in intensity of treatment could be a result of changes in medical technology. The supply side cost changes could also lead to redistribution of resources in hospitals. For example, it might be the case that under PPS Victorian hospitals are managing their patients within the trim points of the LOS i.e. trim points are benchmarks that help hospitals focus on LOS efficiency. Unfortunately, the lack of data availability makes it almost impossible to empirically test the impact of such factors on the inter-DRG resource allocation at the present time.

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Table 1: Summary Statistics: Balanced Panel of DRGs

Variables		Mean	Std. Dev.	Min	Max
Proportions (%)					
Inliers					
	overall	0.386	0.494	0.000	4.311
	between		0.467	0.026	2.794
	within		0.164	-1.577	3.953
High Outliers					
	overall	0.043	0.119	0.000	3.204
	between		0.080	0.000	0.957
	within		0.088	-0.914	2.882
Shares (%)					
Inliers					
	overall	0.448	0.573	0.000	4.970
	between		0.542	0.030	3.234
	within		0.189	-1.757	4.727
High Outliers					
	overall	0.437	1.152	0.000	21.686
	between		0.799	0.000	9.519
	within		0.832	-9.082	19.227
N = 16992 (Sample Size)					
n = 177 (Number of DRGs)					
T = 96 (July 1998 to June 2006)					

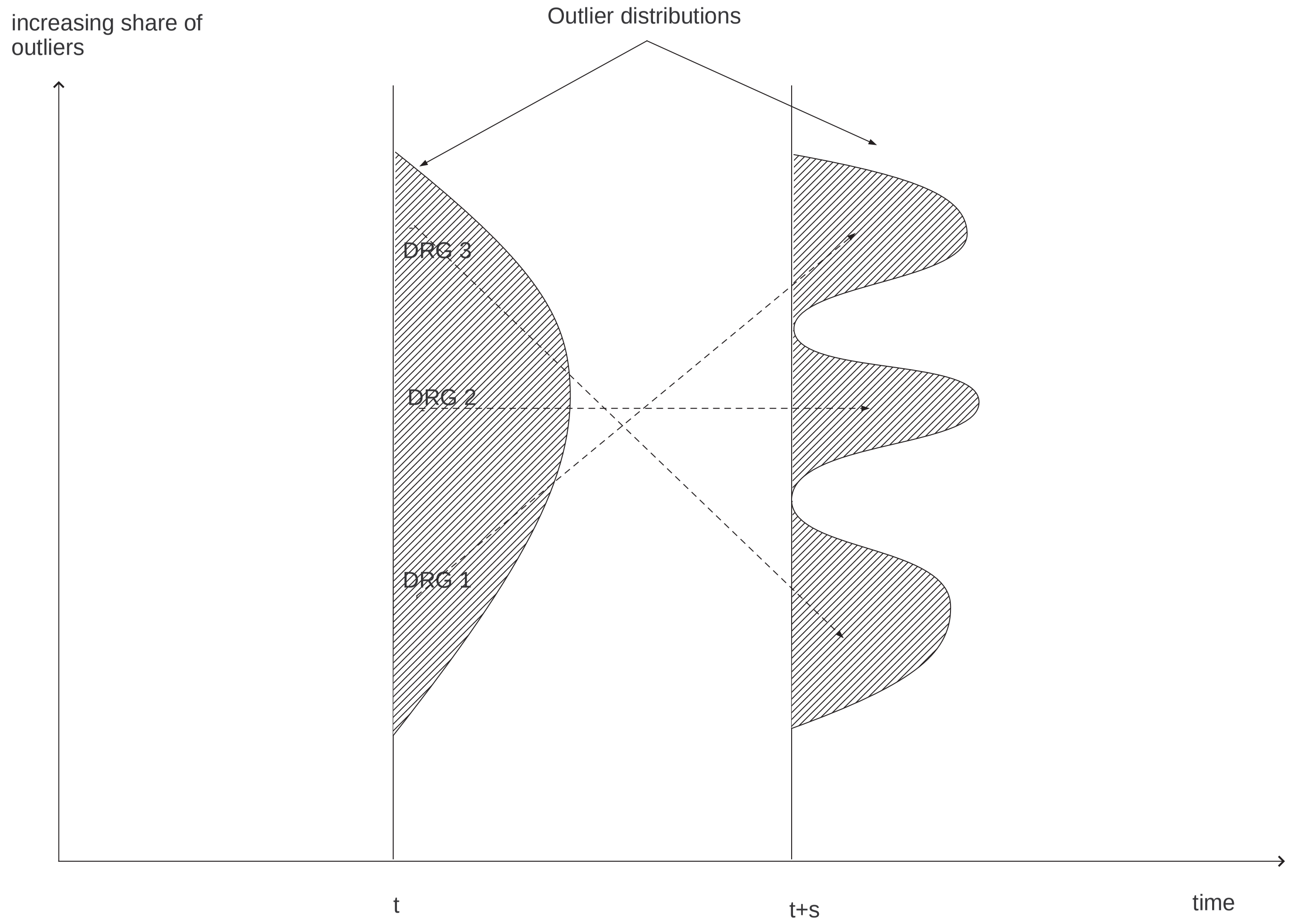


Figure 1: Distributional Dynamics

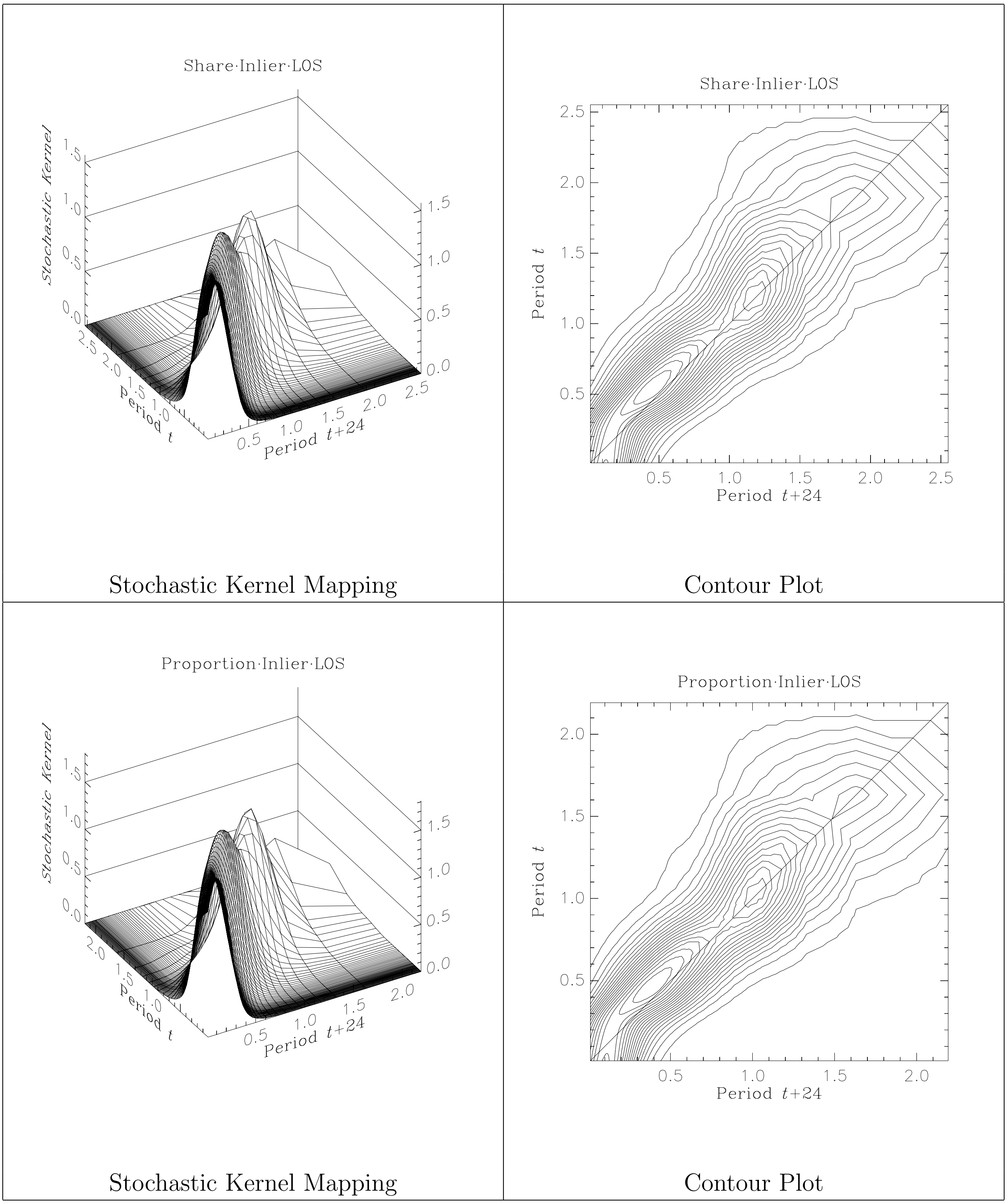
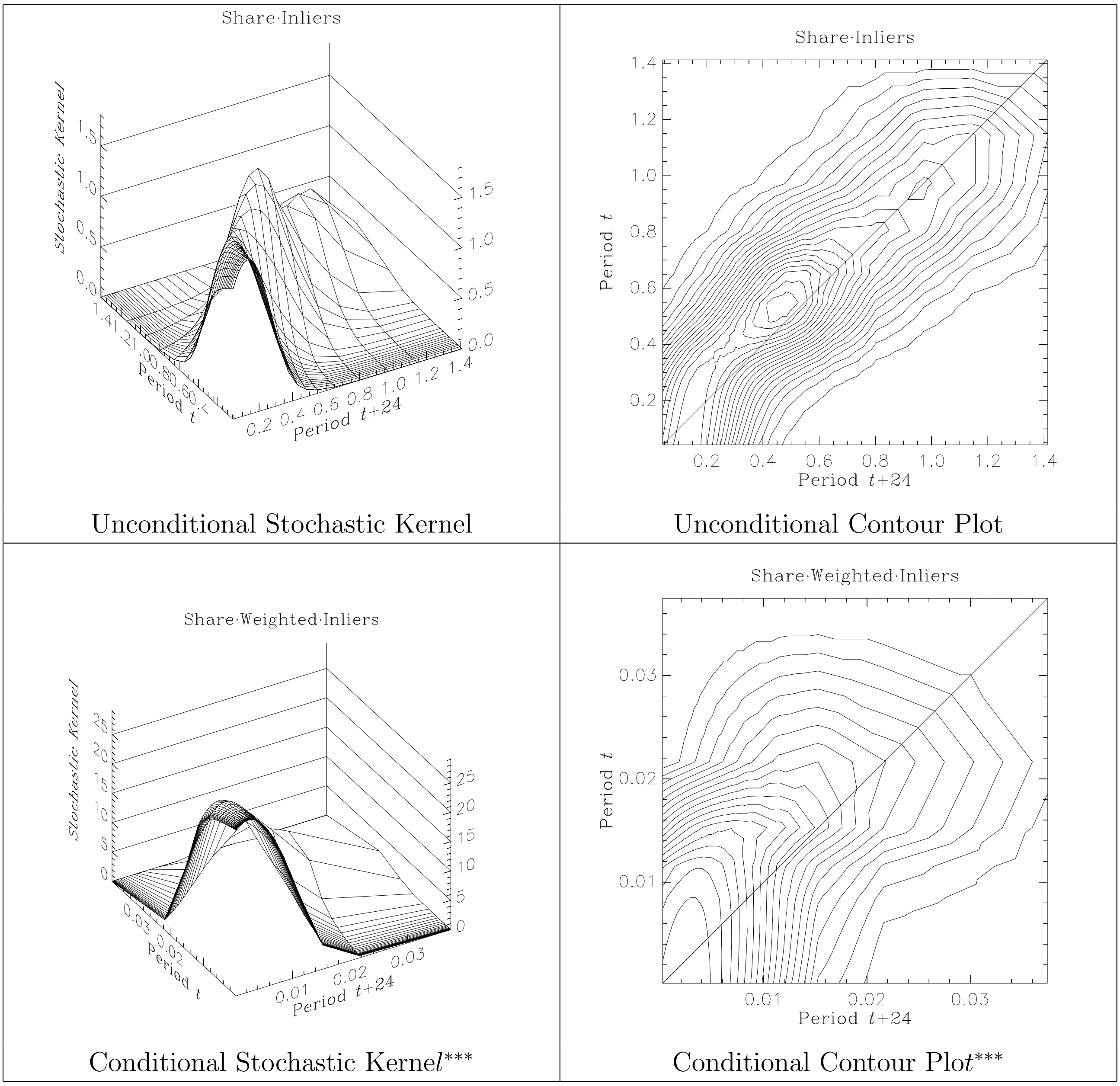


Figure 2: Inliers: Shares and Proportions



***: The axes rescaled by a factor of 10.

Figure 3: Inliers: Shares conditional on Relative DRG prices

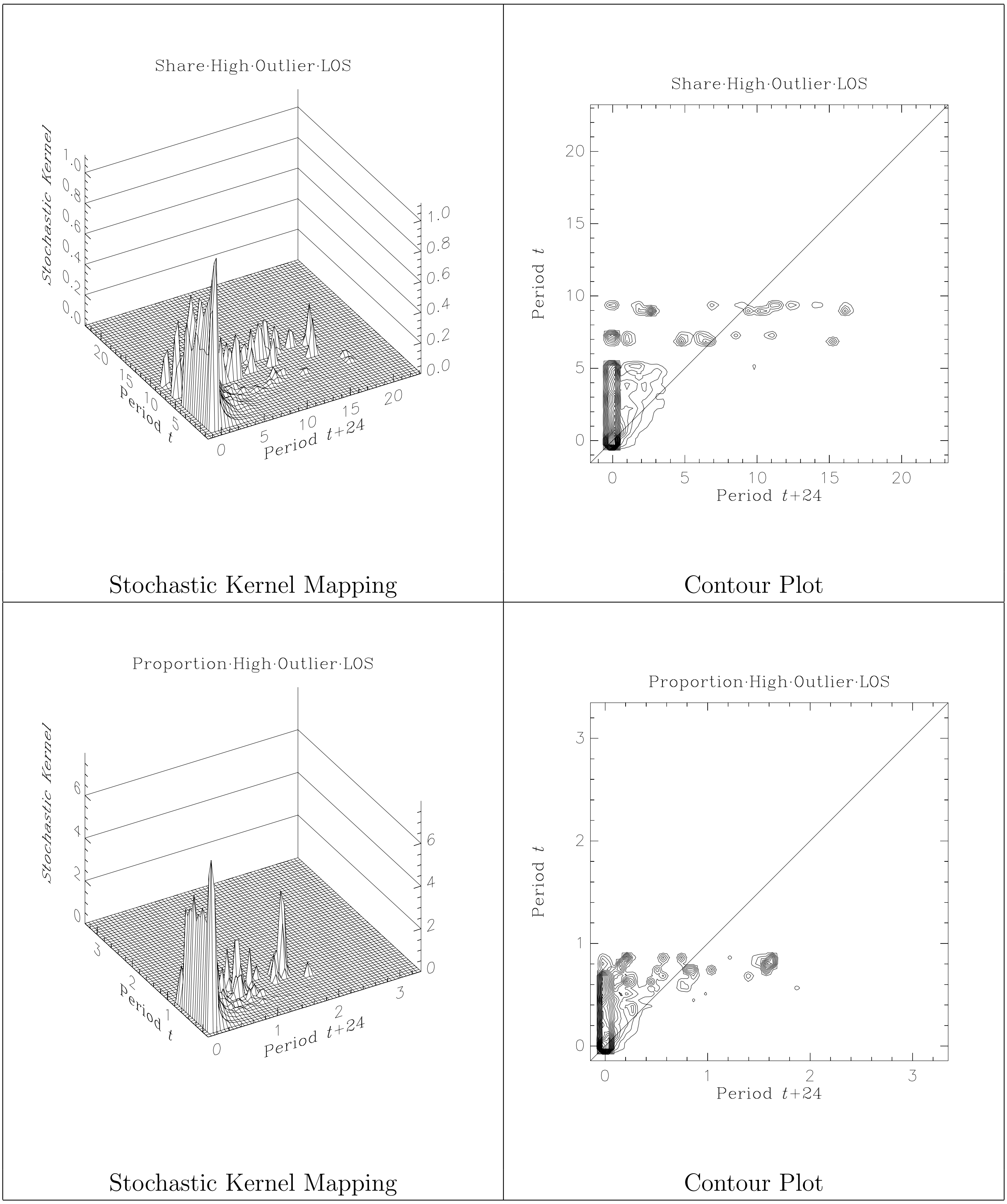


Figure 4: Outliers: Shares and Proportions