Influences of Unemployment Rates and S&P 500 Movements on Eight Selected Individual US Casino Stock Performances

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ABSTRACT

This paper studies the causal effects of changes in unemployment rates and U.S. S&P 500 returns on changes in stock returns of selected eight U.S. casinos individually. Monthly data from January, 1982 through July, 2012 are employed. The time series data in percentage changes are found stationary. As a result, multivariate VAR in first-difference is implemented since the objective is to investigate the effects of changes in causal variables on changes in individual selected casino stock returns. The estimates depict weakly positive and somewhat mixed causal influences of changes in unemployment rates on changes in casino stock returns. In the case of the changes in S&P 500, the results are uniformly positive and relatively strong. In other words, the latter unleash stronger influence than the former on changes in casino stock returns with mixed net short-run interactive feedback effects.[1]

INTRODUCTION

Casino stocks, in general, are considered sin stocks like tobacco and alcohol stocks. Socially responsible, ethical, and environment-friendly investors tend to avoid them in their portfolios. However, such investors seem to enjoy gaming, tobacco and alcohol regardless of economic conditions and political tensions (Berman, 2002; Ahrens, 2004; and Waxler, 2004). Sin stocks, as a whole, are defensive ($\beta < 1$) but casino gaming stocks seem to be more aggressive ($\beta > 1$).[2] Thus, these stocks individually outperform the stock market during bad times because of limited risk sharing. Their excess returns, in general, are higher when the overall stock market is down than when the market is up. The casinos use more private debt than equity

[1] Keywords: Casino Stock Returns, Unemployment Rates, S&P 500 Returns, Unit Roots, and Granger Causality.
[2] β is a measure of systematic risk as in Capital Asset Pricing Model (CAPM) by Sharpe (1964).

financing, and they have superior financial reporting quality than other stock issuing entities. In short, casino stocks add "sizzles" to securities portfolios of individuals.

The casino gaming is a multi-billion dollar industry in the USA. In 2010, total casino gaming revenue was flat at $57.5 billion as compared to 2006. This is expected to grow to $73.3 billion in 2015 presenting a cumulative average growth rate of 5 percent during the forecast period of 2011-2015. Actual amounts of US casino gaming revenue for 2006-2010 and the forecast amounts thereof for 2011-2015 are shown in Appendix A-I. In conjunction with it, the trend is shown for the same sub-periods for global casino gaming revenue in Appendix A-II (www.casinoenterprisemanagement.com/january-2012/pwc).

To examine the time series properties of each variable in percentage change form, the DF-GLS test for unit root and the KPSS test for no-unit root are implemented. On the evidence of stationarity of each variable, the VAR model in first-difference is estimated for each selected casino stock returns for short-run causal flows and interactive feedback effects. Usually, VAR is recommended to be estimated in levels for stationary variables. However, first-differencing or overdifferencing of stationary variables for VAR's is also appropriate for robust estimates (Marcet, 2005).

The primary objective of this paper is to investigate the causal influences of changes in unemployment rates and those of the U.S. stock market (S&P 500) returns on the changes in returns of eight selected U.S. casino stocks, individually. This paper is motivated to study whether the stock prices of the selected casinos are countercyclical. The casino stock prices are considered individually to gain some micro-level insight. The remainder of this paper proceeds in sequence as follows: brief review of related literature, empirical methodology, results, and conclusions.

BRIEF REVIEW OF RELATED LITERATURE

Sin stock returns over various phases of business cycle are likely to be less sensitive to business conditions than other stocks. During bad economic times, they also tend to outperform other stocks. Academic research by Hong and Kacperczyk (2009) documented that sin stocks are underpriced with positive alphas[3], consistent with the portfolio theory. They study the performance of sin stocks in relation to the US stock market over the period of 1965-2003. Based on an unconditional four-factor model which controls for market premium, size, book-to-market and past returns, they argue that sin stocks outperform the stock market because they are not

[3] A positive alpha means outperformance and a negative alpha means underperformance of a stock against its benchmark index.

held by institutions subject to social norms. While gauging the relative importance of litigation risk versus this neglected-stock effect, the authors find that litigation risk cannot explain the abnormal returns on sin stocks. This neglect-effect implies risk-sharing with higher expected returns. Further, Hong and Kacperczyk (2009) study the financing decisions of sin companies and find that they use more private debt financing than equity financing. Kim and Mohan (2006) examine whether this neglected effect is attributable to differential information risk for these firms. They show that sin firms' financial reporting quality is superior to a control group of firms due to greater regulatory scrutiny.

Hong and Kacperczyk (2009) form a sin-stock portfolio and compare its average return to an industry-comparable portfolio. The performance of sin stocks over the business cycle has not been examined from an industry point of view, except for gaming stocks. Goodall (1994) studies gaming stock returns over a 20-year horizon, and find that they tend to be more volatile than the market as a whole. In addition, some special events can cause the gaming stocks to move in a direction opposite to the general stock market. The above results are driven by the relatively small capitalization of these stocks. In addition, this study shows that gaming stocks are more sensitive to stock market declines. Chen and Feng-Shun (2001) study U.S. gaming stock returns over up and down markets, using CAPM regression with time-varying alphas and betas, in a GARCH estimation framework. They show that investors earned negative excess return at an above-market-average systematic risk for holding stocks of gaming companies over 1993-1997. After changes in market conditions were considered, however, the investors in gaming stocks gained a relatively normal return at an abnormal level of risk as compared to the market average systematic risk. But the excess return on sin stocks was higher during down markets than during up markets. They also investigate the effects of legislation events on gaming stock returns, and find that small casino operators are more reactive to deregulation/regulation actions in comparison with large casino gaming firms.

Fabozzi, et al., (2008) examine the issue of how social values affect economic values. Based on a small subset of the stock universe that has been generally associated with sin-seeking activities, such as alcohol consumption, adult services, gaming, tobacco, weapons, and genetic engineering, the authors find that a sin-stock portfolio produced an annual return of 19% over the study period, unambiguously outperforming common benchmarks in terms of both magnitude and frequency. Several likely reasons for the positive excess returns in sin stocks are identified. The authors argue that trustees or fiduciaries who develop institutional investment policy statements should fully understand the economic consequences of screening out stocks of companies that produce a product inconsistent with their value systems. In general, stock returns and unemployment rate reveal causality that runs from stock market to unemployment (Geske and Roll, 1983). Causality between unemployment and Small Cap Returns has also been investigated in Moscarini and Postel-Vinay (2010). They find a distinctly similar cyclical pattern in both large cap and small cap stock performances. Both papers thus underscore the importance of the inclusion of unemployment in this study relating to stock market returns. More recently, Farsio and Fazel (2013) investigate the relationship between unemployment rate and stock prices in USA, China and Japan challenging the assertion that unemployment rate is a strong predictor of stock prices (Little, 2010 and Wojdylo, 2009). They conclude analyzing the data over the 1970-2011 period that it would be a mistake to rely on unemployment rate data to make investment decision in stock market.

EMPIRICAL METHODOLOGY

In general functional form, the estimating model is as follows:

$$Y_t = f\left(\underset{(+)}{U_t}, \underset{(+)}{X_t}\right) \tag{1}$$

where,

Y_t = individual casino's monthly stock return,

U_t = monthly U.S. unemployment rate, and

X_t = monthly return on S&P 500.

The expected sign of causal flow of each explanatory variable is indicated underneath. The time series properties of each variable are investigated by implementing the modified Dickey-Fuller test (DF-GLS) following Elliot et al. (1996), and Ng and Perron (2001). The KPSS test as its counterpart is also applied following Kwaitkowski et al., (1992). The DF-GLS test is about data non-stationarity for the null hypothesis of unit root in each time series variable while the KPSS test is about the null hypothesis of no-unit root in each time series variable. Testing for nonstationarity of each time series variable is essential to ascertain the application of a correct estimating technique since the application of OLS on nonstationary variables leads to the problem of spurious correlation inducing bias and inefficiency in the estimated parameters (Granger and Newbold, 1974).

On the evidence of stationarity in each time series variable, the following VAR model in first-difference is estimated in line with (Granger, 1998) for individual stock return:

$$\Delta Y_t = \alpha + \sum_{n=1}^{n} {}_1\pi_2 \, \Delta Y_{t-i} + \sum_{i=1}^{K} \theta_i \Delta U_{t-i} + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + e_t \tag{2}$$

Here, e = error term, t = time subscript, i = represents optimum number of lags and Δ = first-difference operator. The estimated coefficients of the lagged explanatory variables and their statistical significance display short-term causal flows to the dependent variable with net interactive feedback effects. The optimum lag-lengths are determined by the Final Prediction Error (FPE) criterion following Akaike (1969) to overcome the problems of over-parameterization and under-parameterization that may also induce bias and inefficiency in the estimated parameters. Time Series data on Macroeconomic variables can be nonstationary in levels with the first order of integration, but not cointegrated. In this case, a multivariate VAR with first-differencing of variables in a single equation captures short-run dynamic causal effects with interactive feedback (Bahmani and Payesteh, 1993).

The VAR-family has several variants in levels or in first-difference of variables included in the estimating model(s). A multivariate VAR is natural extension of the standard univariate VAR. A shortcoming of the standard framework for Granger causality is that it only allows for examination of dynamic interactions between single (univariate) variables within a system, perhaps conditioned on other variables. However, interactions do not necessarily take place between single variables but may occur among groups or "ensembles" of variables. This study thus establishes a framework for Granger causality in the context of causal interactions among three variables (Barrett et al., 2010). Moreover, Multivariate VAR often provides superior forecasts to those from univariate time series models requiring less a priori information (Gujarati, 1995). The time profile causal impacts of unexpected shocks or innovations to specific variables on the variables in the model are usually summarized with impulse response functions within the VAR-frameworks for business-cycle analyses (Greene, 2007 and Watson, 1994). A historical variance decomposition of variables is also useful to assessing the driving forces of cyclical fluctuations in VAR-form (Gali, 1999, and King et al., 1991). Transfer Function is an alternative to VAR that does not require either impulse response or variance decomposition analysis. This is used in intervention analysis, but it may be of a little practical value due to unduly high over parameterization (Newbold and Bos, 1990).

Monthly data on all variables are collected from January, 1982 through July, 2012. The data source includes Ameristan Casinos Inc (ASCA: NASDAQ GS).

Brief descriptions of the eight selected U.S. casinos are provided in Appendix B. In addition to data availability, they have been selected for broader geographic network, market capitalization and significant sales volumes.

RESULTS

The simple correlation coefficients of 8 selected U.S. casino stock returns and causal variables (u_t and x_t) are reported as follows:

As observed in Table 1, the pair-wise simple correlation coefficients of casino stock returns are positive. The magnitudes are from moderate to high. However, they may change across sample periods due to changes in macro-economic conditions. Furthermore, correlation does not imply causality. As observed above, the simple correlation coefficient between unemployment rates and S&P 500 returns is positive and very low at 0.1761 suggesting very marginal multi-colinearity for linear dependence of explanatory variables. Both unemployment rates and S&P 500 returns are exogenous as they are generated outside the equation of interest (Engle, Hendry and Richard, 1983).

Next, the time series properties of each variable are examined by implementing the DF-GLS and the KPSS tests. The results are reported as follows:

Table 1
Correlation Matrix
Sample: (January, 1982 - July, 2012)

Country	EC_t	$P_{max,t}$	$P_{rec,t}$	$P_{cut,t}$	$\Delta P_{max,t}$	$\Delta P_{prec,t}$	$\Delta P_{cut,t}$	ΔGDP_t	**constant**	
	UER (U)	S&P 500 (X)	LVS (Y1)	WYNN (Y2)	MGM (Y3)	PENN (Y4)	MTN (Y5)	CAKE (Y6)	ASCA (Y7)	PNK (Y8)
UER (U)	1.0000									
S&P 500 (X)	0.1761	1.0000								
LVS (Y1)	0.1960	0.6774	1.0000							
WYNN (Y2)	0.1472	0.6431	0.8238	1.0000						
MGM (Y3)	0.1133	0.5165	0.8062	0.7708	1.0000					
PENN (Y4)	0.0597	0.5950	0.5125	0.4641	0.5443	1.0000				
MTN (Y5)	0.0847	0.6545	0.6698	0.6132	0.6536	0.5347	1.0000			
CAKE (Y6)	0.2242	0.6392	0.6609	0.5324	0.5557	0.5761	0.6200	1.0000		
ASCA (Y7)	0.0805	0.5247	0.6257	0.5629	0.6085	0.6853	0.5835	0.6718	1.0000	
PNK (Y8)	0.1454	0.5450	0.6188	0.6554	0.6771	0.6354	0.5720	0.5771	0.6305	1.0000

Table 2
Unit Root Tests

	LEVEL	
SERIES	**DF-GLS**	**KPSS**
UER *(U)*	-11.61586*	0.30350**
S&P 500 *(X)*	-14.6874*	0.06925**
LVS (Y_1)	-3.8239*	0.09700**
WYNN (Y_2)	-9.6807*	0.06920**
MGM (Y_3)	-16.8845*	0.02330**
PENN (Y_4)	-14.4548*	0.04381**
MTN (Y_5)	-11.5055*	0.051941**
CAKE (Y_6)	-12.0066*	0.06118**
ASCA (Y_7)	-13.6191*	0.08659**
PNK (Y_8)	-19.5814*	0.03380**

* Significant at 1% level. ** Less than the critical values of 0.739, 0.463, and 0.347 respectively at 1%, 5%, and 10% levels of significance failing to reject the null hypothesis of no unit root.

Table 2 reveals that the null hypothesis of unit root for DF-GLS test is clearly rejected at 1% level of significance (as indicated by *). For KPSS test results, the null hypothesis of no unit root cannot be rejected at 1, 5 and 10 percent levels of significance (as indicated by **). Thus, there are clear evidences of stationarity in all the variables, based on the aforementioned tests. To note, non-stochastic explanatory variables are strongly exogenous for all the parameters (Greene, 2007).

The impulse response analyses due to a given external shock by one standard deviation in S&P 500 returns and unemployment rates unleash short-lived effects on individual casino stock returns (Appendix - C). The historical variance decompositions of variables depict modest and decaying variability, as evidenced in Appendix - D.

Finally, the VAR model, as outlined in equation (2), is estimated for changes in each individual selected casino stock returns. The results are reported in Table 3. A close inspection shows that changes in each casino stock returns are influenced positively and more pronouncedly by changes in the overall US stock market returns than by those in US unemployment rates with two exceptions. They are revealed in coefficients and their associated t-values for individual casino stock returns. The respective sums of the contemporaneous and lagged coefficients of the changes in S&P 500 returns and unemployment rates indicate mixed net short-run interactive feedback effects.

CONCLUSIONS

The selected eight U.S. individual casino stock returns are influenced positively by movements in the US stock market (S&P 500) returns. Six stocks are positively and weakly influenced by the changes in unemployment rates with one-period lag, while two stocks are negatively and weakly influenced. In short, the evidences are somewhat mixed in this regard. Comparatively, the U.S. stock market returns unleash positive influences on the selected eight casino stock returns with greater strength. The influences of changes in unemployment rates on these stock returns are weak and inconclusive to some extent. So, changes in unemployment rates appear not to be a good predictor of Casino stock returns. In closing, the findings of this paper to draw any general and firm conclusion on the countercyclical behavior of casino stock returns should, therefore, be weighed with due caution.

Table 3
Vector Autoregression Estimates*

Independent Variables	Dependent Variables							
	ΔLVS	ΔWYNN	ΔMGM	ΔPENN	ΔMTN	ΔCAKE	ΔASCA	ΔPNK
	0.163157	-0.003258	0.136441	0.043225	0.006303	0.061192	0.065227	-0.095297
ΔUER(t-1)	[1.01728]	[-0.03354]	[1.69558]	[0.63272]	[0.12514]	[1.13034]	[[0.84313]	[-1.58507]
	-0.202364	0.013112	-0.122262	-0.04454	0.000272	-0.068113	-0.056879	0.057257
ΔUER(t-2)	[-0.80801]	[0.13268]	[-1.50194]	[-0.64124]	[0.00531]	[-0.85353]	[-0.50858]	[0.63241]
	0.054901					0.012638	-0.01308	0.050253
ΔUER(t-3)	[0.33073]					[0.22751]	[-0.16271]	[0.81348]
	1.867006	1.647634	1.579487	0.253447	0.752606	0.547392	0.684454	0.209191
ΔSP500(t-1)	[2.17675]	[3.27956]	[5.05666]	[0.97777]	[3.98035]	[2.47194]	[2.45642]	[0.91434]
	-1.280736	-0.420048	-0.031909	-0.597796	-0.361592	-0.186819	-0.514566	-0.419322
ΔSP500(t-2)	[-1.44484]	[-0.82690]	[-0.09846]	[-2.30187]	[-1.85086]	[-0.84044]	[-1.81429]	[-1.85582]
	-0.213329					-0.238714	-0.344708	-0.055748
ΔSP500(t-3)	[-0.23206]					[-1.07661]	[-1.20767]	[-0.24459]
	0.259437							
ΔLVS(t-1)	[1.53432]							
	-0.275894							
ΔLVS(t-2)	[-1.77869]							
	0.241215							
ΔLVS(t-3)	[1.53350]							

		-0.223088						
ΔWYNN(t-1)		[-1.74842]						
		-0.33383						
ΔWYNN(t-2)		[-0.26534]						
			-0.203511					
ΔMGM(t-1)			[-3.01960]					
			-0.167522					
ΔMGM(t-2)			[-2.55316]					
				-0.031163				
ΔPENN(t-1)				[-0.40631]				
				-0.007795				
ΔPENN(t-2)				[-0.10191]				
					-0.193895			
ΔMTN(t-1)					[-2.28875]			
					-0.173066			
ΔMTN(t-2)					[-2.07071]			
						-0.063796		
ΔCAKE(t-1)						[-0.81341]		
						-0.122099		

ΔCAKE(t-2)						[-1.59867]		
						-0.086038		
ΔCAKE(t-3)						[-1.12905]		
							-0.013229	
ΔASCA(t-1)							[-0.17394]	
							-0.007951	
ΔASCA(t-2)							[-0.10375]	
							0.015254	
ΔASCA(t-3)							[0.20365]	
								0.049297
ΔPNK(t-1)								[0.72239]
								0.058984
ΔPNK(t-2)								[0.87573]
								-0.044218
ΔPNK(t-3)								[-0.65376]
	-0.081524	-0.0181149	-0.066204	0.04146	-0.02311	-0.013477	0.044455	-0.055658
C	[-0.87807]	[-0.30014]	[-1.28792]	[1.01314]	[-0.82799]	[-0.41264]	[0.96223]	[-1.45382]

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Appendix A-I

Trend in US Casino Gaming Revenue and Forecast for 2011-2015

(In millions of U.S. dollars)

Region	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2011-15 CAGR
Nevada	12,783	13,017	11,599	10,393	10,405	10,700	11,135	11,652	12,290	12,955	
%Change	8.4	1.8	-10.9	-10.4	0.1	2.8	4.1	4.6	5.5	5.4	4.5
Atlantic City	5,218	4,920	4,545	3,943	3,565	3,300	3,080	2,945	2,870	2,815	
%Change	4.0	-5.7	-7.6	-13.2	-9.6	-7.4	-6.7	-4.4	-2.5	-1.9	-4.6
Tribal Casinos	24,889	26,143	26,739	26,482	26,503	27,500	28,800	30,200	31,750	33,350	
%Change	10.6	5.0	2.3	-1.0	0.1	3.8	4.7	4.9	5.1	5.0	4.7
Regional Casinos	14,580	16,360	16,550	16,550	17,015	18,000	19,300	20,700	22,200	24,200	
%Change	6.4	12.2	1.2	0.0	2.8	5.8	7.2	7.3	7.2	9.0	7.3
Total	57,470	60,440	59,433	57,368	57,488	59,500	62,315	65,497	69,110	73,320	
%Change	8.4	5.2	-1.7	-3.5	0.2	3.5	4.7	5.1	5.5	6.1	5.0

Appendix A-II

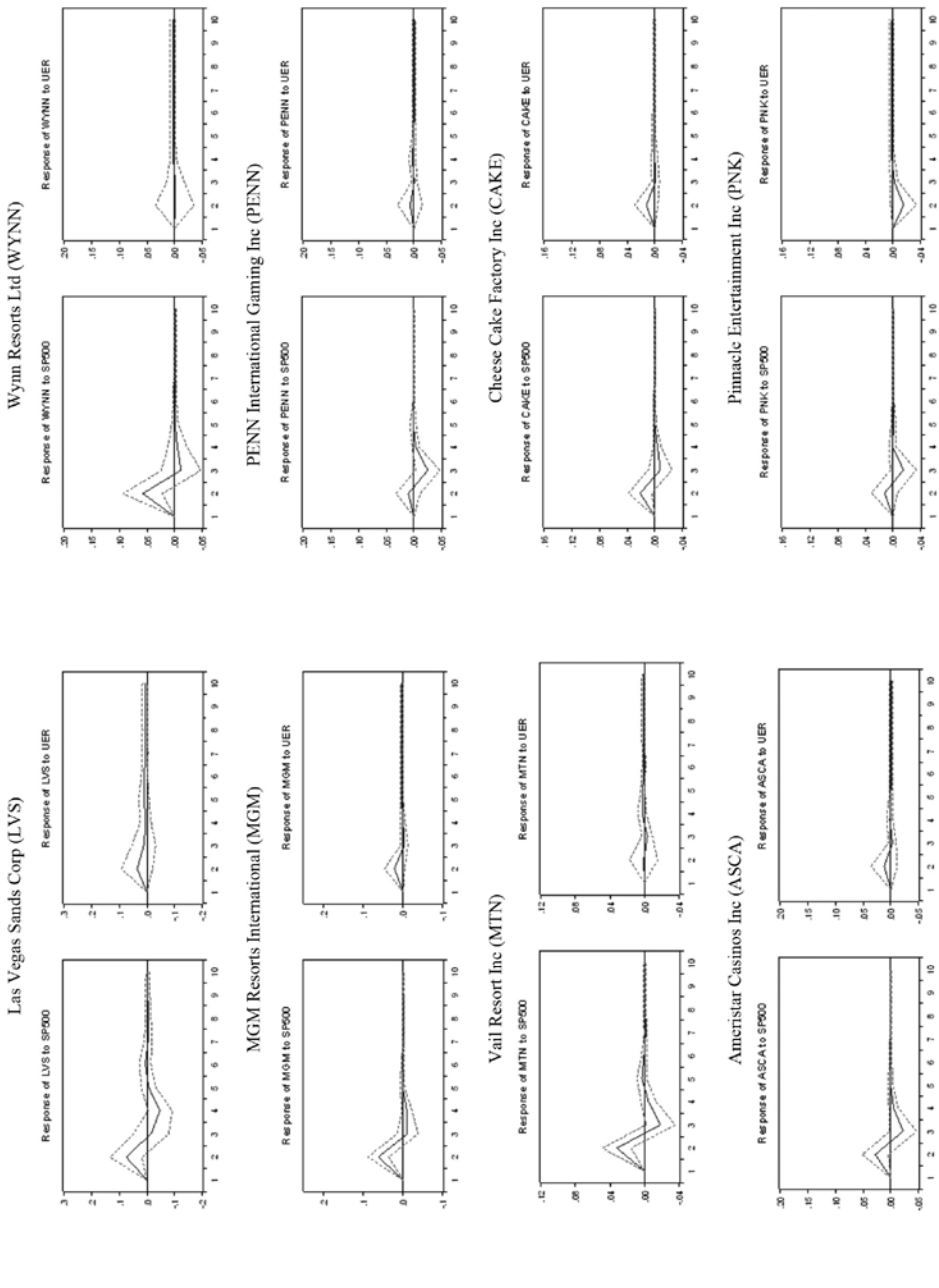
Trend in global Casino Gaming Revenue and Forecast for 2011-2015

(In millions of U.S. dollars)

Region	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2011-15 CAGR
United States	57,470	60,440	59,433	57,368	57,488	59,500	62,315	65,497	69,110	73,320	
%Change	8.4	5.2	-1.7	-3.5	0.2	3.5	4.7	5.1	5.5	6.1	5.0
EMBA	20,783	20,894	19,959	17,567	16,307	16,175	16,250	16,751	17,350	18,343	
%Change	2.8	0.5	-4.5	-12.0	-7.2	-0.8	0.5	3.1	3.6	5.7	2.4
Asia Paeifle	13,687	17,714	21,379	22,898	34,280	47,042	58,124	66,961	73,429	79,266	
%Change	16.3	29.4	20.7	7.1	49.7	37.2	23.6	15.2	9.7	7.9	18.3
Latin America	2,584	2,959	3,269	3,601	3,800	4,096	4,370	4,757	5,165	5,614	
%Change	25.6	14.5	10.5	10.2	5.5	7.8	6.7	8.9	8.6	8.7	8.1
Canada	5,354	5,685	5,694	5,874	5,704	5,597	5,621	5,743	5,986	6,230	
%Change	10.7	6.2	0.2	3.2	-2.9	-1.9	0.4	2.2	4.2	4.1	1.8
Total	99,878	107,692	109,734	107,308	117,579	132,410	149,680	159,709	171,040	182,773	
%Change	8.7	7.8	1.9	-2.2	9.6	12.6	10.8	8.9	7.1	6.9	9.2

Source: PWC's Global Gaming Outlook to 2015

Appendix – C
Impulse Response Analyses
(Cholesky one S.D. Innovations ± 2 S.E.)



Appendix – D*
(Variance Decomposition)

Period	LVS	SP500	UERT	WYNN	SP500	UERT	MGM	SP500	UERT
1	100.0000	54.60635	97.09281	100.0000	66.76188	98.09241	100.0000	87.15146	98.85982
2	90.51346	54.32615	91.66303	89.59059	66.65921	96.90424	90.17890	86.94624	98.00191
3	90.4058	54.54306	85.84413	89.21286	66.62580	95.26516	90.08870	86.43206	96.36560
4	87.96060	54.52154	83.35304	89.12828	66.58635	94.51489	89.90130	86.43445	95.47362
5	87.80111	54.46828	81.62695	89.09794	66.55145	94.04317	89.87807	86.41042	94.87447
	PENN	**SP500**	**UERT**	**MTN**	**SP500**	**UERT**	**CAKE**	**SP500**	**UERT**
1	100.0000	84.81632	99.24152	100.0000	80.28590	98.68751	100.0000	77.46783	96.62351
2	99.35613	83.89858	97.78851	91.14689	78.98725	97.88498	96.30515	76.69635	95.55421
3	96.75777	83.86002	96.45739	88.96034	78.44522	96.11749	96.01368	75.23382	92.69365
4	96.68642	83.82149	95.39437	88.75713	78.44599	94.66115	95.92575	75.18518	91.27252
5	96.67909	83.80669	94.88521	88.67402	78.40180	93.91521	95.92263	75.15242	90.30716
	ASCA	**SP500**	**UERT**	**PNK**	**SP500**	**UERT**			
1	100.0000	90.93304	97.23716	100.0000	90.07670	98.38769			
2	96.82768	89.82326	91.50307	98.22475	89.80383	98.30454			
3	95.19142	89.68803	87.01515	97.17818	89.14996	96.65522			
4	95.09882	89.66734	84.70897	97.16522	89.09608	95.71233			
5	95.09697	89.65677	83.26654	97.13834	89.07643	95.00617			

*Cholesky Ordering

APPENDIX – B*

The Cheesecake Factory Inc (CAKE) is traded on NASDAQ and is headquartered in Calabasas Hills, California. Its primary businesses include restaurant and bakery operations. The Company has approximately 170 restaurants operating nationwide. The market capitalization was 2.01 billion dollars in 2012. Sales and income are growing at close to a 3% rate. The sales have been 1.81 billion dollars in the last year.

Pinnacle entertainment Inc. (PNK) is traded on the NYSE and headquartered in Las Vegas, Nevada. The company is an owner, operator and developer of casinos and related entertainment facilities. The company operates in several states as well as Asia. Their market capitalization was $852.37 million in 2012. Sales were 1.2 billion dollars in the last year. Income growth was negative for the period but the sales growth has been almost 5%.

Ameristar Casinos Inc. (ASCA) is traded on NASDAQ and headquartered in Las Vegas. The company has 8 casinos in seven different markets in the US. In July of 2012 it purchased Creative Casinos of Louisiana in its entirety. The market capitalization for Ameristar was $864.51 million in 2012. Sales have been 1.2 billion dollars in the last year. The growth rate in sales has been slightly negative but the income growth rate has been over 1,000%

Vail Resort Inc. (MTN) is traded on the NYSE and headquartered in Colorado. Vail is a holding company consisting of operations in Mountain (ski Resorts), lodging and Real Estate. They acquired several new properties in 2012. Their Market capitalization was 2.22 billion dollars in 2012. Sales were $1.07 billion in the last year. The growth rates in sales and income were negative for the last year.

Penn National Gaming Inc. (PENN) is traded on NASDAQ and is headquartered in Pennsylvania. Penn is the owner and manager of gaming properties and race tracks throughout the US and in Canada. The market capitalization for the company was $4.24 billion in 2012. Sales in the last year were $2.9 billion. The growth rate in sales was almost 6%, but the growth rate in income was negative.

MGM Resorts International (MGM) is traded on NYSE and headquartered in Las Vegas. The company is engaged primarily in the gaming business with 15 resorts in the US and more in China under the name MGM Macau. The market capitalization of the firm was $6.29 billion in 2012. The Sales in the last year was $9.16 billion. The growth rate in sales was 17%, and the income growth rate was negative for the period.

Wynn Resorts Ltd (WYNN) is traded on NASDAQ and headquartered in Las Vegas. The company is a developer, and operator of casino properties. The company operates in Las Vegas and in Macau. The market capitalization of the company was $12.48 billion last year. The last year's sales were $5.15 billion. The growth in sales for the period was slightly negative and the growth in income was more negative (18.2%).

Las Vegas Sands Corp (LVS) is traded on the NYSE and is headquartered in Las Vegas. The company is a developer of destination properties in the US and China. The market capitalization of the company was $45.95 billion in 2012. The last year's sales figures were $11.13 billion. The sales growth and income growth rates for LVS were around 20%.

BIOGRAPHICAL SKETCH OF AUTHORS

Dr. Matiur Rahman is a Professor of Finance and MBA Director at McNeese State University. He earned his Ph.D. in economics from Southern Methodist University, Dallas, Texas. He is a prolific researcher and published numerous theoretical and empirical articles in refereed U.S. and foreign journals in economics, finance and international business.

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*As abbreviated in Table 1 are shown in parentheses.