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Long Run Equilibrium and Short Run Dynamics Between Risk Exposure and Highway Safety

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Abstract

Based upon monthly California data from January 1981 through December 1998, this analysis uses vector error correction methodologies and associated statistical tests to identify the long run relationship and, after controlling for various policy relevant variables, to explore the short run dynamics between highway vehicle miles traveled and highway crashes. The analysis finds that there is a cointegrating relationship between vehicle miles traveled and crashes and, for fatal, serious injury, and materials crashes, could not reject the hypothesis that crash exposure and crash frequency move proportionately. Among the policy implications are that higher speed limits had non-positive effects on highway safety and alcohol availability was an important determinant of crashes. The analysis also finds that crashes respond to deviations in vehicle miles traveled from the long run trend more quickly for the more serious crashes. This exploratory analysis indicates that vector error correction models may be an important tool for improving our understanding of highway crashes and the near and longer term impacts that alternative policies will have on highway safety.

JEL Classification: R40, R41, C22.

Keywords: Traffic Accidents, Cointegration, Error Correction.

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1 Introduction

Exposure to risk is a necessary condition for highway crashes to occur. Regardless of methodological approach - paired comparisons, regression-based frameworks, time series modeling - virtually all empirical highway safety studies either explicitly (e.g. through independent variables) or implicitly (e.g. experimental versus a control group, crash rates) account for the effects of exposure to highway risk. However, notwithstanding the large empirical literature on highway safety, there are relatively few studies that report crash elasticities with respect to vehicle-miles-traveled (VMT), a commonly used measure of risk exposure. The evidence that exists suggests that highway safety generally but not uniformly experiences economies with respect to VMT (see, Crandall et al. 1986, Zlatoper 1984, McCarthy 2000, 2005, Gaudry and Lassarre (Eds., 2000), Hu et al. 1998 among others).

With few exceptions, most empirical studies that include VMT as an explanatory variable model the long run relationship, ignoring potentially important short run impacts that changes in VMT may have upon crashes. Scuffham (2003) developed and estimated a structural time series model, a generalized ARIMA model that explicitly incorporates flexible structures for trends and seasonality as well as short run dynamics. Based upon New Zealand quarterly data from 1970 through 1994, Scuffman's results imply a 1.39 long run elasticity of fatal crashes with respect to vehicle kilometers traveled (VKT).

In this paper, we propose an alternative approach to examine the relationship between VMT and highway safety. Rather than imposing the assumptions inherent in a given structural form, we posit a long-run equilibrium relationship between crashes and exposure to crashes using a vector error-correction model (VECM). Reassuringly, a long-run relationship between the variables is consistent with the mere fact that without exposure, there shouldn't be any crashes. In our VECM, we test for the existence of a long-run relationship between crashes and VMT using cointegration tests. We estimate and test the magnitude and sign of the long-run elasticity of different crash types with respect to exposure and use Granger casuality tests and forecast error variance decompisitions to further evaluate the short run and long run dynamics between crashes and exposure. In our VECM, we also control for the effect of various policy and business cycle variables as well as seasonality.

Our empirical results identify important and interesting dynamic characteristics, both in the short run and in the long run, of the relationship between exposure and crashes. Findings reported in the paper indicate that several measures of crashes and exposure are cointegrated and hence tend to move around a common trend in the long run despite some deviations in the short run. We find evidence in support of exposure being an important source of various crashes. Analysis of variance decompositions reveal that changes in exposure have persistent effects on various crashes, especially in the long run.

2 Methodology

We conduct our analysis on the dynamic relationship between crashes and exposure in four distinct steps. First, we test for nonstationarity in the data. The time series need to have the same order of integration for the cointegration tests to be valid. A process is said to be integrated of order d, denoted by $I(d)$, if it has to be differenced d times before it becomes stationary.[1] A unit root is when a series is integrated of order one and thus needs to be differenced once to be stationary.

We use two univariate unit-root tests: the DF_{GLS} test of Elliott, Rothenberg, and Stock (1996) and the KPSS test of Kwiatkowski, et al. (1992). The advantage of the DF_{GLS} test is that it has significantly higher power than previous versions of the augmented Dickey-Fuller test. The DF_{GLS} test has a null hypothesis of a unit root, while the KPSS test has a null hypothesis of stationarity. By using unit-root tests with different nulls, we do not make any a priori assumptions on the stationarity of the series. We include an intercept and time trend term in each test to allow for drift in the time series. For DF_{GLS} test, we use the sequential testing procedure suggested by Ng and Perron (2001) to determine the lag length where the maximum lag number was set by the Schwert (1989) method. For the KPSS test, we use the

[1]For formal definitions of stationarity and related issues as well as the details of methodology, see Hamilton (1994) and Johansen (1995).

automatic bandwidth selection routine of Hobijn et al. (2004).

In the second step, we use the maximum-likelihood procedure of Johansen (1995) to test for cointegration. A set of variables is said to be cointegrated if a linear combination of the individually integrated series, $I(d)$, is stationary. In our case, $Y_t = (crash_{j,t},\ exposure_t)$ represents a (2×1) vector of $I(1)$ time series. Y is cointegrated if there exists a (2×1) vector β such that

$$\beta' Y_t = \beta_{crash_j} crash_{j,t} + \beta_{exp} exposure_t \sim I(0). \tag{1}$$

The linear combination $\beta' Y_t$ is referred to as a long-run equilibrium relationship. The intuition is that an $I(1)$ time series with a long-run equilibrium cannot drift too far apart because economic forces will bring it back to that long-run equilibrium. The Johansen procedure begins with a vector autoregression (VAR) model of order p for Y_t and by using the Granger representation theorem (Granger and Engle 1997) develops a vector-error correction model (VECM). Johansen (1995) proposes two types of log-likelihood ratio tests to determine the number of cointegrating vectors r in the VECM. The maximum eigenvalue test uses the maximum generalized eigenvalue of $\alpha\beta'$ (where α is the 2×1 loading or speed of adjustment parameters) to test the null hypothesis that the cointegration rank is at most r against the alternative that the cointegration rank is $r + 1$. The trace statistic test, on the other hand, uses the trace of the diagonal matrix of generalized eigenvalues of $\alpha\beta'$ to test the null hypothesis that the cointegration rank is at most r against the alternative that the cointegration rank is s. The null hypothesis of rank $r = 0$ (i.e. no cointegrating relationship) is first tested and, if rejected, subsequent null hypotheses ($H_0 : r = 1$, $H_0 : r = 2$, etc.) are tested until a null can no longer be rejected. When the rank is deemed to be r, then there are r cointegrating vectors.

In the third step, if the variables are found to be cointegrated, we can then estimate a vector error-correction model. The VECM for crashes in equation form is:

$$\Delta crash_{j,t} = \mu + \sum_{i=1}^{p-1} \delta_i \Delta crash_{j,t-i} + \sum_{i=1}^{p-1} \gamma_i \Delta exp_{t-i} + \alpha \times ect_{t-1} + u_t, \tag{2}$$

where μ, δ_i, γ_i, and α are coefficients to be estimated and u_t is a white noise series. In the equation, $ect_{t-1} = \beta' Y_{t-1}$ is an $(r \times 1)$ error-correction vector and α is a $(1 \times r)$ vector of speed of adjustment coefficients. The coefficients in front of the lagged difference terms capture the short-run dynamics in the system, while α for the error-correction term represent the adjustment of $\Delta crash_{j,t}$ towards its long-run equilibrium $\beta' Y_t$. One can also include a constant and trend term in the cointegration relation ect_{t-1}, (Johansen 1995). Note that since $\beta' y_{i,t}$ measures the long-run equilibrium for a particular vector i, then the α parameter will measure the size of the contemporaneous change as the system moves back to equilibrium. One potential problem with the Johansen methodology is that α and β cannot be uniquely identified. However, for $r = 1$, α and β can be uniquely identified with a normalization. We normalize on the $crash_j$ so that $\beta = (1, \beta_{exp})'$. Therefore, for $r = 1$, the error-correction term ect_{t-1} becomes $(crash_{j,t-1} + \beta_{exp} exp_{t-1})$ and the coefficients in (2) can be uniquely estimated.

With the cointegrating relationship $\beta' Y_t$ in vector format and normalized on the $crash_j$ variable, β_{exp} are expected to be negative if there is a positive long-run relationship between different crash types and exposure to crashes. Similarly, the expected sign of α is negative. Given that a positive error-correction term ect_{t-1} represents a deviation of crashes relative to exposure from their common trend, α should be negative so that crashes declines relative to exposure to restore the long-term relationship.

The lag length (p) is chosen by the Akaike, Hannan-Quinn, and Schwartz-Bayesian information criteria as well as sequential testing procedures suggested in Ng and Perron (2001) to insure a parsimonious fit. The estimated residuals in (2) must have no serial correlation, no conditional heteroskedasticity, and not deviate too much from Gaussian white noise for the estimation to be consistent and asymptotic distribution theory to be used in conducting inference. We therefore test for residual autocorrelation, autoregressive conditional heteroskedasticity, and normality of the residuals using Portmanteau, LM, and Jarque-Bera tests, respectively.[2]

In the fourth step, we run a series of tests on the coefficients in the $crash$ equations (2). We test for the significance of the normalized cointegrating vector β. The coefficients $-\beta_{exp}$ measure the long-run relationship between the different crash measures and exposure as measured by

[2]We have reported results from the models that passed the mentioned diagnostic tests. Full estimation results can be obtained upon request.

VMT. We also test for the significance of α or weak exogeneity in different crashes. Weak exogeneity in (2) means that the crash j does not react to disequilibrium (or deviation from the long term common trend between crash j and exposure). A rejection of the null of weak exogeneity implies a long-term relationship between the $crash_j$ and $exposure$. In addition, we test for strong exogeneity: the joint significance of the lags of each explanatory variable and the lagged error-correction term. If the null of strong exogeneity is rejected, this implies Granger causality. In Eqn. (2), we test for Granger causality of exposure ($H_0 : \alpha = \delta_1 = \cdots = \delta_{p-1} = 0$).

In order to gain further insights into the short run and long run dynamics between different crashes and exposure, lastly, we compute forecast error variance decompositions from our VECM. Variance decompositions give the proportion of the movements in the dependent variables that are due to their own shocks versus those that are due to the other variable(s). A shock or innovation to exposure, for example, directly affects exposure but the shock's effect will also flow through each of the other variables in the system through the model's dynamic structure.

3 Empirical Results

3.1 Data, unit root, stationarity and cointegration

The primary data for this analysis consists of monthly observations on the number of crashes that occurred on California roads and the number of highway miles traveled on state highways. The sample period is January 1981 through December 1998. We employ seven measurements to characterize highway safety on California roads. In particular, our set of variables includes: logarithm of total monthly crashes ($crash_T$); total fatal crashes ($crash_F$); total injury crashes ($crash_I$); total serious crashes ($crash_S$); total other injury crashes ($crash_O$); total complaint-of-pain crashes ($crash_P$); and total materials damage only crashes ($crash_M$). Exposure (exp) refers to the logarithm of state highway miles traveled per month. The analysis also controls for the effects of business cycle and socioeconomic factors (unemployment rate, logarithm of per capita labor income, logarithm of real gasoline price), the environment (rainfall, temperature), and policy relevant variables (speed limit changes, increased penalties for driving under the influence (DUI) of alcohol, changes in administrative per se DUI and a measure of alcohol license density).[3]

Columns 2 and 3 of Table 1, present the unit-root and stationarity tests for *crash* measures and our measure of *exposure*. We include a constant and trend term in each test. DF_{GLS} test fails to reject the null of a unit root in all series, while $KPSS$ test rejects the null of stationarity in all series at 1% significance level. The unit root and stationarity tests suggests that all crash types and exposure have a unit root.[4]

Next, we use the Johansen maximum-likelihood estimator to test for the number of cointegrating vectors between different crashes and exposure to crashes. The optimal lag length (p) is eight (eight lags in levels and seven lags in differences) for all pairs of crashes and exposure. We present the maximum eigenvalue and trace statistics in last four columns of Table 1. Since, over the sample period, *exposure* exhibited an increasing (linear) trend around a drift, we include a constant and a trend term in testing for cointegration. Presented in second panel of Table 1, the values of the trace and maximum eigenvalue statistics soundly reject the null hypothesis of no cointegration (i.e. $r = 0$). The trace test and the maximum eigenvalue tests show that *crashes* and *exposure* are cointegrated at 1 or 5 percent significance level for all pairs of exposure and crashes and hence a linear combination of $crash_j$ and *exposure* are trend stationary.

3.2 VECM Estimation Results

In Tables 2 and 3 we display summary of the estimated VECM for different *crash* types and *exposure* from the models of the form given in (2). In addition to several business cycle and environment related factors, the models also include dummy variables to identify the effect

[3]State highway miles include all roads that the state of California maintains, including Federal Interstate routes. The CA Highway Patrol provided crash data, the CA Department of Alcohol Beverage Control provided alcohol license data, the CA Department of Finance provided population data, the CA Department of Labor provided unemployment rates, and the Department of Motor Vehicles provided driver license data. California Department of Transportation (CALTRANS) provided VMT data and the Bureau of Economic Analysis provided income data. CA government websites and websites for various federal and highway safety organizations provided data on highway safety regulations.

[4]Not reported, we have also tested unit root null and stationarity in our control variables. Overall, results suggest stationarity of control variables. These results can be obtained upon request.

of alternative policy relevant factors. In May 1987, California raised the speed limit on rural interstate highways from 55mph to 65 mph. And in January, 1996 California allowed 70mph on portions of its interstate highway system. In January, 1982 California implemented Assembly Bill 541 which raised various penalties associated with driving under the influence of alcohol. And in January 1990, California implemented Senate Bill 1119, which reduced the BAC administrative per se level from .10 to .08. Last, the analysis includes the alcohol license density, which captures the effect of alcohol availability. We have also included monthly dummy variables to control the seasonal effects.

Table 2 reports estimates for the adjustment parameter, cointegration vector as well as results for the Granger causality tests. The point estimate, standard error, and significance level of the loading coefficient α are presented on the left-most panel. The loading coefficient has the expected negative sign and is significant in all different crash types. Suppose that type j crashes in month t are above the long run equilibrium identified by the cointegrating relationship between $crash_j$ and $exposure$. Estimated adjustment coefficient indicates that type j crashes next month should decrease to adjust towards the long run cointegration relationship. From a behavioral standpoint, the reduction in type j crashes is consistent with motorists facing a higher risk price and responding in various safety enhancing ways (e.g. reduced speeds, longer headways, less weaving in and out of traffic). The results also reveal that the speeds of adjustments are not uniform across crash types but adjust more quickly for the more serious crashes. There is a much steeper decline in fatal, serious injury and, somewhat surprisingly, materials only crashes in the following month, (above 50%) than in crashes involving injuries that were less serious.

The larger drop for more serious crashes suggests that drivers respond more quickly to their long run cointegrating relationship when changes in the traveling environment have greater implications for these types of crashes. Consider, for example, an increase in the number of drinking drivers (due, for example, to reduced taxes on alcohol, reduced enforcement, an increase in the number of establishments licensed to sell alcohol, or an increase in a population cohort - “baby boomers” - with more idle time) that produces an unexpected rise in drinking and driving-related crashes involving serious injuries and fatalities. This would lead drivers to alter their behaviors quickly to restore the long run relationship between VMT and crashes.

From Table 2 and Equation (1), the estimated cointegration relationship (normalized such that the coefficient on crashes is unity (Johansen 1995)) between different crash types and exposure have a monthly trend over our sample period with the trend coefficient estimate ranging between 0.003 and 0.006. In particular, all else constant, there is a 0.3 - 0.6% monthly decrease or 3.6%-7.2% annual decrease in total highway crashes over the sample period. In addition, and as expected, the long run relationship between highway exposure and each crash type is positively related after simultaneously controlling for short run dynamics and for the influences of policy relevant variables, environmental factors, and the business cycle. Estimated cointegration vectors indicate that the (long-run) elasticity of crashes with respect to exposure ranges between about 0.86 and 2.32. The reported Likelihood Ratio statistics that test the null hypothesis of unit elasticity (i.e. tests the cointegration vector to be $(1, -1)$) fails to reject unit elasticity in four out of seven crash measures, supporting the hypothesis that the crash elasticity with respect to VMT is constant and unity especially for more serious crashes. Careful inspection of results indicate that, when injury crashes occur, the fatal and serious injury crashes increase less than proportionately with increases in VMT but that increases in non-fatal injury crashes increase more than proportionately and increasingly so as the level of crash severity declines.

The significance levels of the Granger-causality tests are presented on the last column of Table 2. The reported marginal significance levels suggest significant evidence on Granger-causality of exposure to crashes. Recall that Granger causality tests whether the past values of a variable (i.e. $exposure$) help explain the current value of a variable (i.e. $crash_j$). At the very least, Granger causality describes the temporal relationship between the two variables (Granger, 1969). However, if an underlying economic framework is also present, then Granger-causality tests can provide evidence about the direction of true causation (see Hamilton, 1994, for an example).[5] Obviously if there is no exposure, there wouldn't be crashes. This framework should

[5] The voluminous money-income causality literature pioneered by Sims (1972) attests to the potential of

lend our VECM approach insight into the causal relationship between crashes and exposure. As a result, our Granger causality tests may well be revealing evidence on the true source of the different crashes. And the results in Table 2 may argue that not only is exposure is an important temporal source of the variation in different crashes, but it is also an important causal source.

3.3 Forecast Error Variances Decompositions

In order to gain insights into the dynamic evolution of relationship between crashes and exposure, Table 3 reports the forecast error variance decompositions for a forecasting horizon that runs from 1 through 60 months. From Table 3, each series explains the preponderance of its own past values, especially in the short forecast horizons. Depending upon the crash type, variation in exposure explains about 11% to 27% of forecast error variance of crashes after a two year period. The further out the forecast horizon, the more of the forecast error variance in crashes does exposure explain. After three years, more than 50% of forecast error variance of total crashes, fatal, serious and materials crashes are explained by the exposure. This indicates that overtime, exposure becomes more and more important in explaining the forecast error variation in crashes, especially for more serious crashes than less serious type of crashes after controlling for short run-dynamics and other exogenous factors.

3.4 Policy-Related Effects on Crashes

Focusing on short run dynamics for crashes in Table 4, we see that the two speed limit laws generally reduced crashes. From the results, raising speed limits from 55mph to 65mph on rural interstate highways had no impact on fatal or serious injury crashes but reduced crashes in all other categories. Further relaxation of speed limits in 1996 had only statistically significant negative effects on complaint of pain and injury crashes.

Some of the strongest results are seen for the alcohol variables. Increases in alcohol density, a measure of availability, significantly increases all crashes, regardless of severity (only in two

Granger causality.

type of crashes the effects are not significant at conventional levels, namely serious injury and other injury crashes). And lowering the administrative per se BAC level from .10 to .08 (sb1119) increased crashes in all but the "other injury". Interestingly, increased enforcement had little effect on crashes.

With respect to the economic variables, the effects of unemployment rate and per capita labor income were either absent or non-positive. In particular, increases in per capita labor income has no significant effects on crashes while increases in the unemployment rate reduce total crashes, primarily due to its impacts on fatal, serious injury and materials crashes. Increase in gasoline prices reduces the incidence of all crashes, which is not necessarily surprising. And consistent with expectations, inclement weather conditions compromise highway safety, increasing crashes in most categories.

4 Conclusion

In contrast with other studies of highway crashes, this paper focused upon the long term equilibrium and short term dynamics of the relationship between highway crashes and risk exposure. From a unique set of monthly data on California crashes, we tested for the existence of a long-run relationship using the cointegration tests of Johansen (1995). We found strong evidence on existence of a cointegrating relationship between several crash types and exposure with a trend in the cointegrating relationship. We then estimated a vector error-correction model to test the direction of the long-run relationship and for Granger causality. We also included a limited set of control variables to capture the effects of the business cycle and highway safety policy.

We could not reject the hypothesis that there is a proportional relationship between VMT and total, fatal, serious injury, and materials crashes. On the other hand, the results indicated that there exists an elastic long-run relationship (with the elasticity ranging between 1.33 and 2.32) between non-serious injury and complaint-of-pain crashes and exposure. Also, the VECM results indicate that movements in *crashes* adjusts to deviations from the long run relationship between crashes and exposure where the adjustment speed is generally higher for the more serious crash types. Moreover, the findings indicated that exposure Granger-causes all crash types and hence there is evidence of causal effects from exposure to crashes. Variance decompositions showed that exposure tends to explain more than 50% of the variation in more serious type crashes and about 30 to 40% variation in less serious injury crashes in a three-year horizon.

An important implication of this analysis is that VEC models provide new insights into the complex relationship between highway safety and exposure to crashes. Understanding and distinguishing between the long run trend and short run dynamics will assist policy makers in formulating and enacting highway safety policies that have the greatest impact in reducing the frequency and severity of crashes on the nation's highways.

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Table 1: Unit Root and Stationarity Tests for Monthly Data

Series	Unit Root and Stationarity Tests DF_{GLS}	$KPSS$	Cointegration Tests Trace-statistics $r=0$	$r=1$	Max-statistics $r=0$	$r=1$
$crash_T$	-1.649	$0.400^{\ddagger}$	$27.79^{\dagger}$	3.03	$24.75^{\ddagger}$	3.63
$crash_F$	-1.540	$0.367^{\ddagger}$	$36.11^{\ddagger}$	4.72	$31.39^{\ddagger}$	4.72
$crash_S$	-1.635	$0.368^{\ddagger}$	$29.92^{\dagger}$	1.82	$28.10^{\ddagger}$	1.82
$crash_P$	-0.888	$0.499^{\ddagger}$	$26.30^{\dagger}$	6.57	$19.73^{\dagger}$	6.57
$crash_M$	-1.917	$0.331^{\ddagger}$	$26.62^{\dagger}$	3.25	$23.39^{\dagger}$	3.25
$crash_O$	-1.720	$0.393^{\ddagger}$	$35.78^{\ddagger}$	4.94	$30.84^{\ddagger}$	4.94
$crash_I$	-1.122	$0.485^{\ddagger}$	$31.02^{\ddagger}$	4.24	$26.79^{\ddagger}$	4.24
Exposure (exp)	-0.796	$0.496^{\ddagger}$	.	.	.	.

Notes: Columns 2 and 3 report results from the DF_{GLS} and $KPSS$ tests respectively. The 1%, 5%, and 10% critical values for DF_{GLS} are -3.480, -2.890 and -2.570 respectively. The 1%, 5% and 10% critical values for KPSS test are 0.216, 0.146, and 0.119 respectively. ‡ and † indicate significance at 1 and 5 percent levels respectively. Columns 4 through 7 presents cointegration tests (due to Johansen 1995) while the last column gives the results from Horwath-Watson (1994) test for cointegration with a known cointegration vector of $(1, -1)$. For the null of $r = 0$, the 1% and 5 % critical values for the Trace statistic are 30.45 and 25.32 respectively, while for the Maximum-eigenvalue test they are 23.65, 18.96. For the null of $r = 1$, the 1% and 5% critical values are 16.26 and 12.25 respectively for both tests. The 1% and 5% critical values for the HW test are 13.73 and 10.18 respectively. Each test was run with a constant and trend term. The lag lengths are determined by modified AIC and sequential lag selection procedures suggested by Ng and Perron (2001).

Table 2: Summary VECM Results for different crashes and exposure

variables	Adjustment Parameter α α	Cointegration Vector: β $crash_{t-1}$	exp_{t-1}	$trend$	$H_0: \beta = (1, -1)$ p_{LR}	Granger Causality $exp \rightarrow crash$
($crash_T$, exp)	-0.496	1.000	-1.120	0.003	0.240	0.004
	(0.093)[0.000]		(0.179)	(0.001)		
($crash_F$, exp)	-0.571	1.000	-0.960	0.005	0.916	0.083
	(0.126)[0.000]		(0.387)	(0.001)		
($crash_S$, exp)	-0.519	1.000	-0.857	0.005	0.645	0.032
	(0.110)[0.000]		(0.305)	(0.001)		
($crash_P$, exp)	-0.343	1.000	-2.320	0.004	0.000	0.032
	(0.090)[0.000]		(0.237)	(0.001)		
($crash_M$, exp)	-0.531	1.000	-0.980	0.003	0.920	0.001
	(0.089)[0.000]		(0.211)	(0.001)		
($crash_O$, exp)	-0.446	1.000	-1.328	0.006	0.082	0.017
	(0.097)[0.000]		(0.183)	(0.001)		
($crash_I$, exp)	-0.364	1.000	-1.819	0.005	0.000	0.043
	(0.094)[0.000]		(0.176)	(0.001)		

Notes: The VECM results for different crashes and exposure are presented. The estimates, standard errors (in parentheses) and the $p-$values (in brackets) of the loading vector (i.e. adjustment parameters) are shown on the leftmost panel. The null hypothesis tested is the weak exogeneity ($\alpha = 0$). The estimates and standard errors for the normalized cointegration vector with a trend term in the coinegration are given in the middle panel. The $p-$values of the test of strong exogeneity ($\alpha = \delta_1 = \cdots = \delta_{p-1} = 0$) are shown on the rightmost panel.

Table 3: Forecast Error Variance Decompositions

	Variance Decomposition of $Crash_j$ by $exposure$						
forecast error of $\|\| h$	$3-mth$	$6-mth$	$12-mth$	$24-mth$	$36-mth$	$48-mth$	$60-mth$
$crash_T$	0.009	0.031	0.274	0.490	0.576	0.617	0.639
$crash_F$	0.051	0.064	0.160	0.373	0.516	0.584	0.616
$crash_S$	0.020	0.038	0.115	0.414	0.591	0.679	0.728
$crash_P$	0.005	0.037	0.115	0.254	0.298	0.320	0.333
$crash_M$	0.010	0.012	0.244	0.557	0.709	0.777	0.813
$crash_O$	0.020	0.050	0.229	0.353	0.401	0.428	0.437
$crash_I$	0.023	0.042	0.164	0.225	0.281	0.298	0.307

Key: Table reports 3, 6, 12, 24, 36, 48 and 60 months-ahead forecast error variance decompositions of various crashes explained by variation in exposure.

Table 4: VECM Results: Policy and Business Cycle Variables

	Policy Variables				Other Variables						
variables	$ab541$	spd_{87}	spd_{96}	sb_{1119}	$alcden$	$income$	$unemr$	p_{gas}	$precip$	$temp$	R^2
$\Delta crash_{T,t}$	0.025	-0.047	-0.010	0.022	0.392	0.008	-0.012	-0.142	0.014	0.002	0.877
	(0.016)	(0.008)	(0.007)	(0.009)	(0.112)	(0.084)	(0.003)	(0.029)	(0.001)	(0.000)	
$\Delta crash_{F,t}$	0.075	-0.002	-0.020	0.050	0.816	-0.272	-0.020	-0.116	0.003	0.007	0.742
	(0.039)	(0.019)	(0.017)	(0.021)	(0.287)	(0.203)	(0.008)	(0.059)	(0.002)	(0.002)	
$\Delta crash_{S,t}$	0.007	0.017	-0.015	0.034	0.253	0.106	-0.015	-0.160	0.002	0.007	0.817
	(0.026)	(0.015)	(0.011)	(0.014)	(0.202)	(0.128)	(0.006)	(0.045)	(0.002)	(0.001)	
$\Delta crash_{P,t}$	0.007	-0.057	-0.037	0.023	0.335	-0.013	-0.006	-0.105	0.014	0.001	0.837
	(0.021)	(0.012)	(0.010)	(0.011)	(0.149)	(0.104)	(0.004)	(0.033)	(0.001)	(0.001)	
$\Delta crash_{M,t}$	0.011	-0.048	-0.001	0.020	0.513	-0.010	-0.015	-0.162	0.017	0.001	0.872
	(0.019)	(0.009)	(0.008)	(0.010)	(0.134)	(0.095)	(0.003)	(0.032)	(0.001)	(0.001)	
$\Delta crash_{O,t}$	-0.034	-0.054	0.007	0.007	0.171	0.115	-0.004	-0.100	0.004	0.006	0.886
	(0.018)	(0.011)	(0.008)	(0.010)	(0.132)	(0.093)	(0.003)	(0.027)	(0.001)	(0.001)	
$\Delta crash_{I,t}$	0.034	-0.044	-0.019	0.022	0.236	0.019	-0.004	-0.116	0.010	0.003	0.873
	(0.017)	(0.009)	(0.008)	(0.009)	(0.120)	(0.085)	(0.003)	(0.027)	(0.001)	(0.001)	

Notes: VECM estimates and standard errors for the exogenous policy relevant and other control variables are displayed together with the R^2 values.