MACROECONOMIC EFFECTS IN US CORPORATE DEFAULTS:

AGGREGATING REAL ECONOMY EFFECTS DYNAMICALLY

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Overview

- Aim/scope
  - Aggregate dynamically the macroeconomic effects
  - Capture the effect of the macroeconomy on the credit cycle
  - Explore differences in macroeconomic effects on credit cycles across sectors
- Methodology
  - Split macro variables into 11 subsets according to macroeconomic concepts
  - 11 ML dynamic factors for each subset and an overall aggregate macroeconomic factor
  - Latent factor regression of the 11+1 dynamic factors against defaults to capture their effect on credit cycle
  - Regression against sector defaults to capture different credit cycles
- Key Findings
  - Output related factors (business cycle) influence significantly the credit cycle
  - The aggregate dynamic factor is highly significant, indicating the credit cycles depend on the macroeconomic environment
  - Sector credit cycles and macroeconomic effects are significantly different
- Future research

Dynamic Factors

- Pitfalls when using individual macroeconomic variables
  - Misspecification risk: E.g. Fed Funds rate used instead of 3-month treasury bill rate
  - Default is a complicate process and might depend on multiple time series describing the same concept: E.g. Both Fed Funds rate and 3-month treasury bill rate should be used
- Dynamic Factor Models
  - Factor Analysis: Summarize the time variation of multiple time series in a small set of factors
  - Dynamic Factors: Take into account the dynamic evolution of the factors
- 11 Dynamic Factors based on 11 macroeconomic concepts
  - Output, Output Gap, Consumption, Investment, Production, Inflation, Labour Market Conditions, Wages, Cost of Debt, Equity Markets, Money Supply
  - 1 aggregate factor to summarize the macroeconomic variables variation

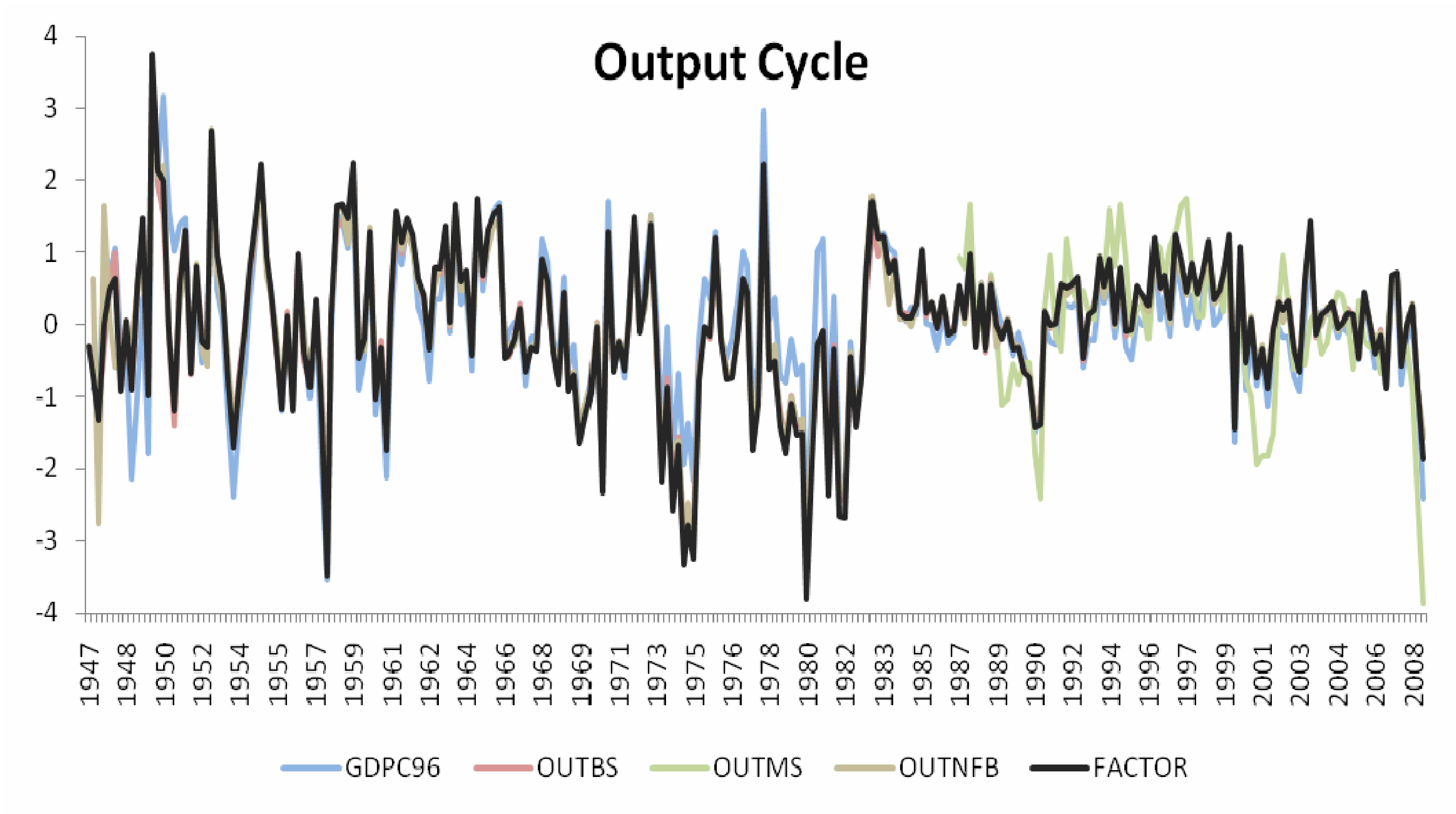
Dynamic Factor Model (DFM)

- DFM form:
$$Y_t = \lambda(L) F_t + \varepsilon_t$$
$$F_t = \Phi(L) F_{t-1} + \eta_t, \quad \eta_t \sim N(0, I)$$
$$\varepsilon_t = \mathrm{P}(L)\varepsilon_{t-1} + v_t, \quad v_t \sim N(0, \Sigma_\varepsilon), \quad \Sigma_\varepsilon = diag(\omega_i^2)$$
- For simplicity we assume that the lag polynomial $\lambda(L)$ does not contain any lags, and that $\Phi(L) = \varphi$, $\mathrm{P}(L) = \rho$ (first order autoregressive processes)
  - The resulting DFM takes the form:
$$Y_t = \Lambda F_t + \varepsilon_t$$
$$F_t = \varphi F_{t-1} + \eta_t, \quad \eta_t \sim N(0, I)$$
$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t, \quad v_t \sim N(0, \Sigma_\varepsilon), \quad \Sigma_\varepsilon = diag(\omega_i^2)$$
- For small n, Kalman Filter and Smoother can be used
  - Kalman Smoother for each of the 11 subsets results in 11 dynamic factors $F_{i,t}, \ i = 1,..,11$
  - Once Y_t^F are estimated they are used as observables to extract the single aggregate factor F_t^A from the DFM:
$$Y_t^F = \Lambda^A F_t^A + \varepsilon_t^F, \quad \varepsilon_t^F \sim N(0, \Sigma_{\varepsilon^F}), \quad \Sigma_{\varepsilon^F} = diag(\omega_{i^F}^2)$$
$$F_t^A = \Phi^A(L) F_{t-1}^A + \eta_t^A, \quad \eta_t^A \sim N(0,1)$$

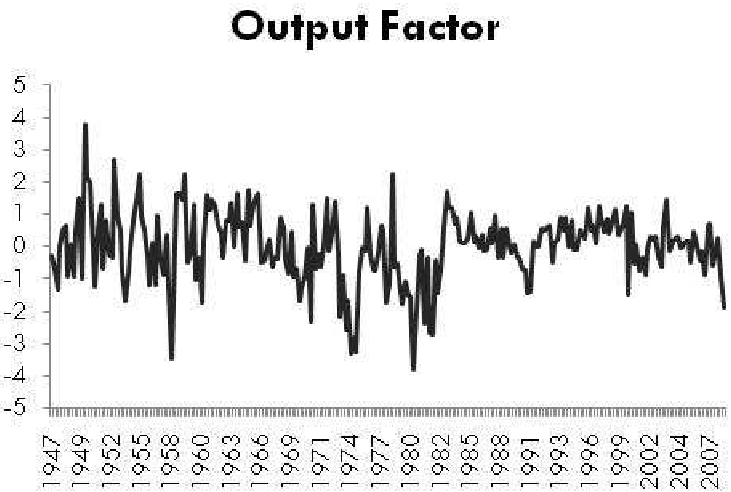
Aggregate Macroeconomic Factor Estimates

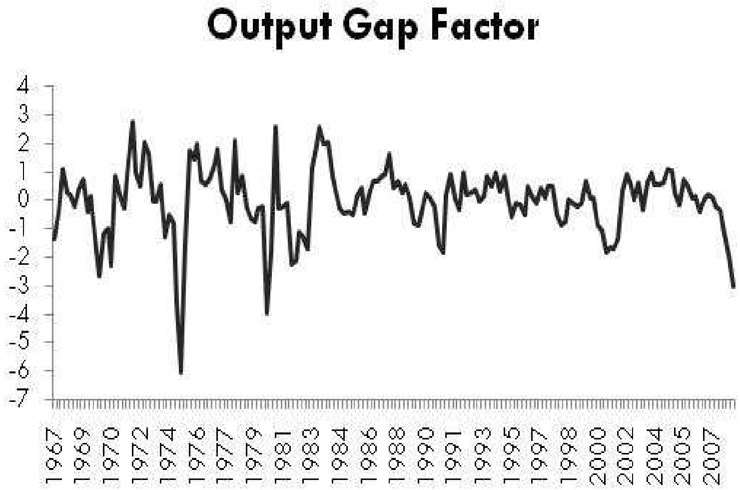
Factor	φ_{factor}	$S.E.\ \varphi_{factor}$	$\omega^2_{\text{variable}}$	$S.E.\ \omega^2_{\text{variable}}$	$\lambda_{\text{variable}}$	$S.E.\ \lambda_{\text{variable}}$
Total	0.6378132570	0.0439934345				
Output			0.3155914860	0.0336891706	0.6378691652	0.0398997088
Output Gap			0.5982380563	0.0526955676	0.4876979110	0.0435728488
Consumption			0.4871845463	0.0450954891	0.5515988859	0.0428831272
Investment			0.3560920366	0.0352019663	0.6185926285	0.0397881102
Production			0.1451888399	0.0193116017	0.7132890299	0.0382929510
Inflation			0.9958954202	0.0798564754	0	0
Labour			0.3097636709	0.0320299525	0.6405952094	0.0388475378
Wages			0.3143732661	0.0308288964	0.6384400405	0.0390051808
Cost of Debt			0.8423314722	0.0716030208	0.3031134195	0.0445675632
Equity			0.9599381272	0.0724219946	0.1465877845	0.0460342399
Money			0.9707886296	0.0476276363	0.1231122232	0.0458097706

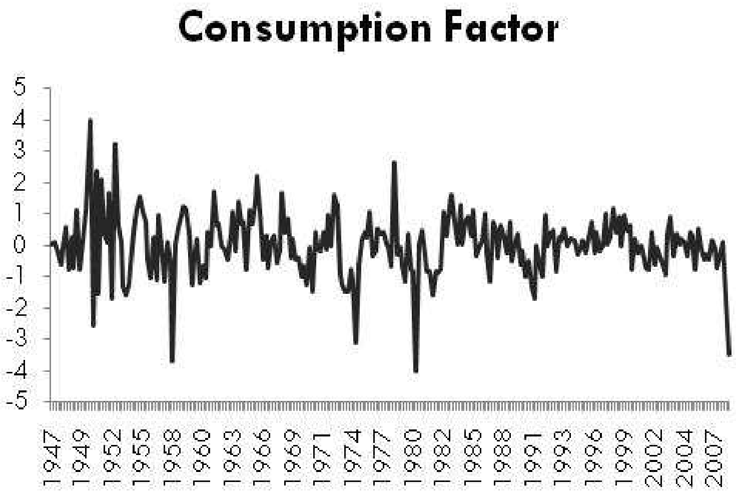
Output Cycle Decomposition

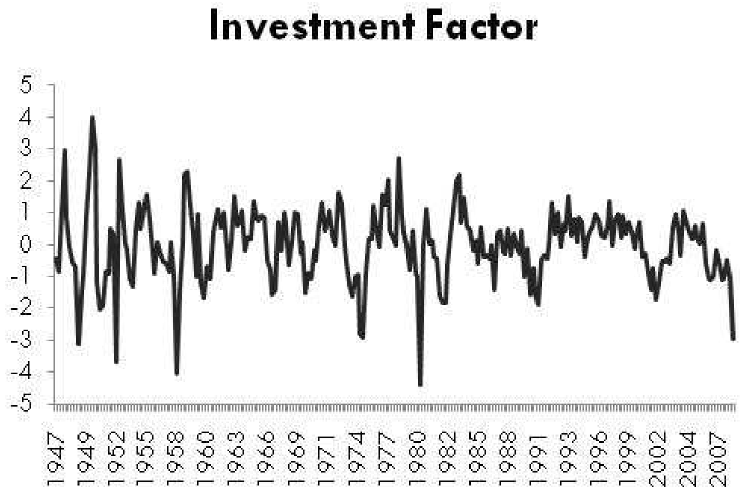


Smoothed Macroeconomic Factors

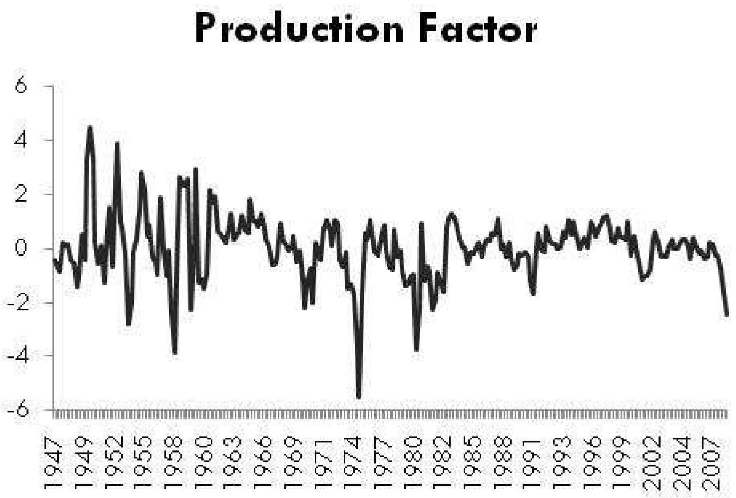


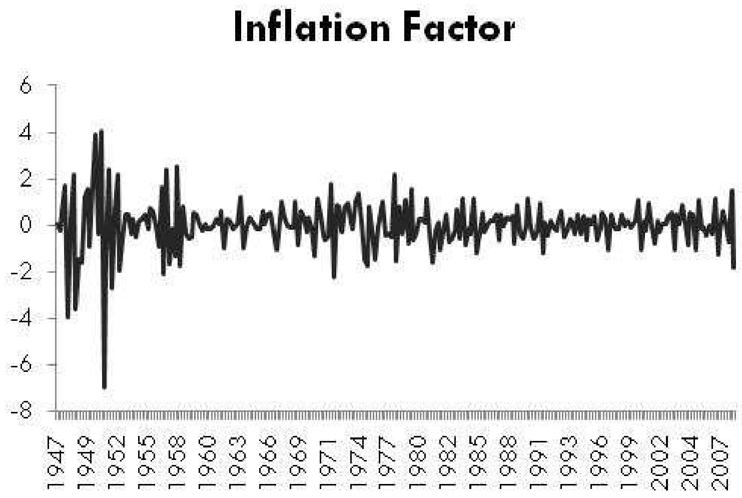




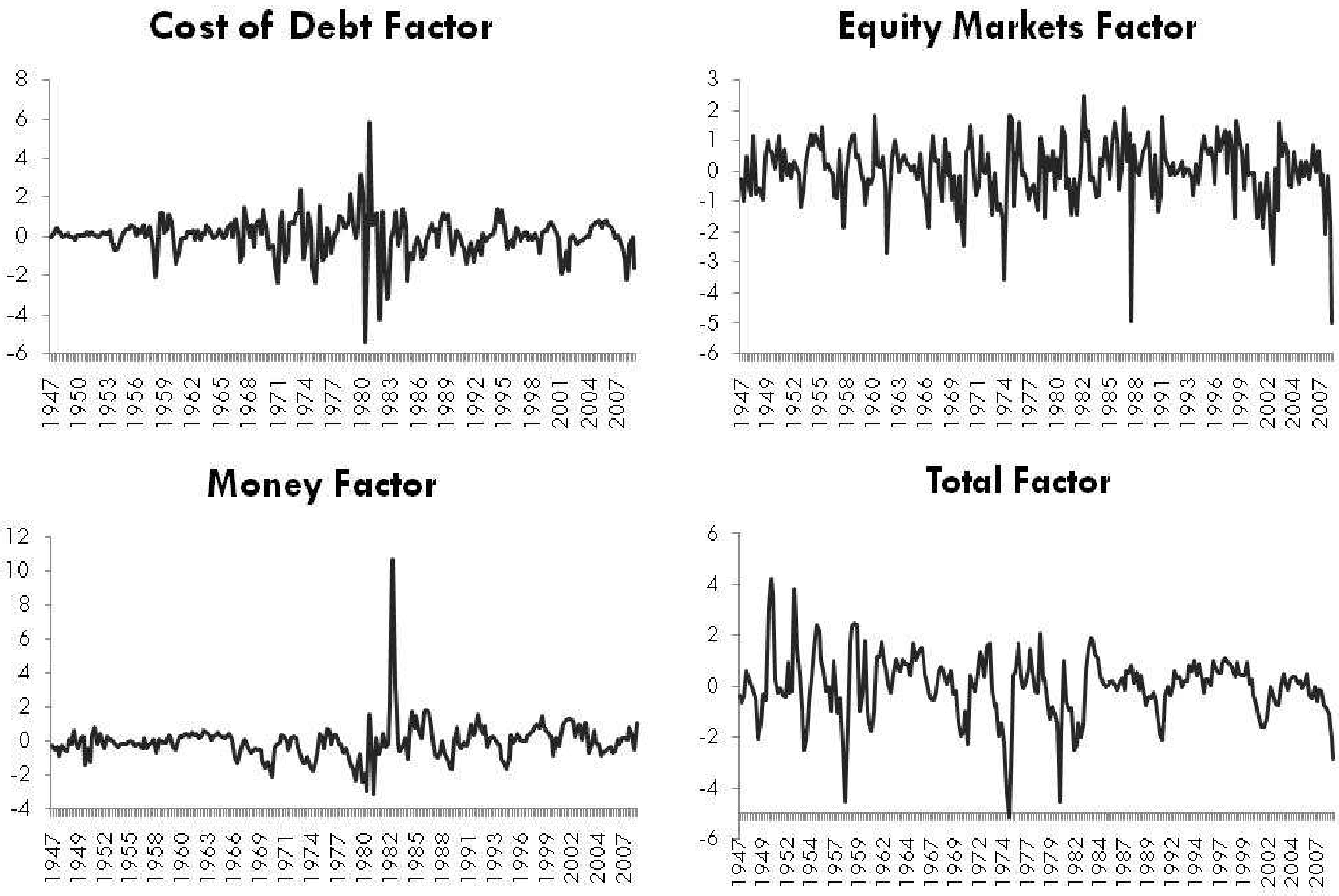


Macroeconomic Factors





Macroeconomic Factors



Default Risk Model

- Aggregate defaults are modeled as follows:

$$D_t \mid X_{it}, u_t \sim Binomial\left(PD_t, N_t\right)$$

$$PD_t = f\left(a + \beta_i X_{it} + u_t\right), \ \ f\left(x\right) = \frac{1}{1+\exp\left(-x\right)}$$

$$u_t = \varphi_u u_{t-1} + e_t, \ \ e_t \sim N\left(0, \sigma_e^2\right)$$

  - X_{it} is the ith macro variable and a the intercept
  - Factor u_t can be considered as an unobservable-latent frailty factor. It can be stationary, if $|\varphi_u| < 1$, or a random walk, if $\varphi_u = 1$
- For the overall economy, the presence of a unit root for the frailty factor cannot be ruled out and a random walk representation is used throughout the analysis.
- For individual sectors, the latent factor is stationary and φ_u is estimated

Default Risk Model Estimation

- Importance sampling simulated likelihood method (Durbin & Koompan 1997,2001)
- Likelihood is approximated by Monte Carlo simulation
  - Importance density is formed by an approximate Gaussian likelihood which has the same slope and curvature with the original non-Gaussian log-likelihood
  - Gaussian likelihood and latent factor are calculated by Kalman filtering and Smoothing
  - Gaussian likelihood is adjusted by the ratio of the Binonial to the approximate likelihood (importance weight)

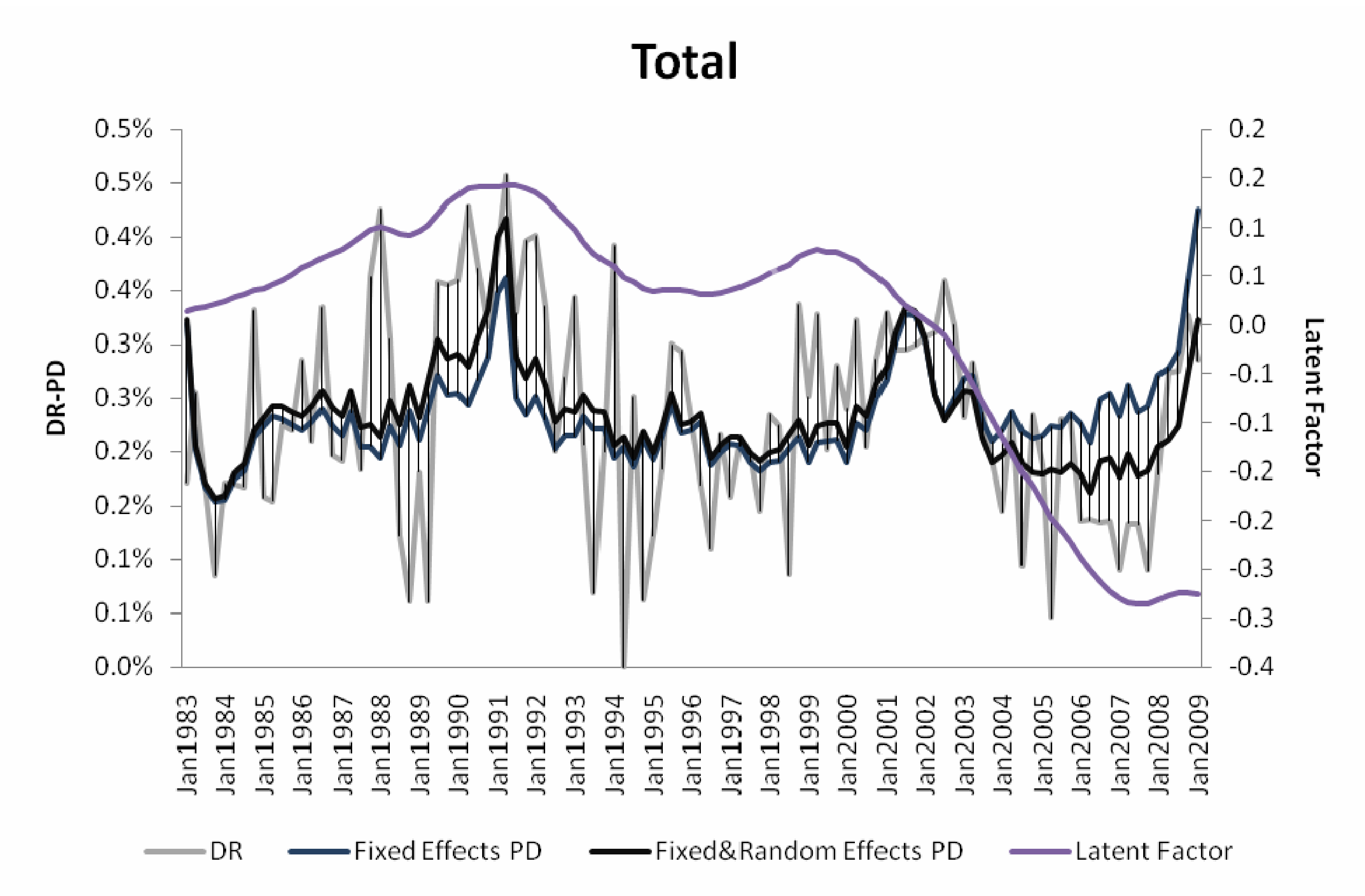
Default Risk Model Estimates

Factor	β_i	$S.E.\ \beta_i$	σ_e^2	Log Likelihood	AIC	BIC
Output	-0.1542	0.0768	0.3002e-2	-211.1676	4.0794	4.1552
Output Gap	-0.1395	0.0575	0.2576e-2	-210.7054	4.0706	4.1464
Consumption	-0.1783	0.0700	0.2934e-2	-210.1426	4.0599	4.1357
Investment	-0.1824	0.0625	0.2119e-2	-209.3943	4.0456	4.1214
Production	-0.1915	0.0787	0.2607e-2	-210.3429	4.0637	4.1395
Inflation	0.0220	0.0794	0.6019e-2	-212.7942	4.1104	4.1862
Labour	-0.2002	0.0510	0.1369e-2	-206.7798	3.9957	4.0716
Wages	-0.0840	0.0574	0.3956e-2	-212.1949	4.0990	4.1748
Cost of Debt	-0.1655	0.0626	0.3069e-2	-209.9242	4.0557	4.1315
Equity Markets	-0.0838	0.0412	0.3756e-2	-211.6342	4.0883	4.1641
Money	0.0389	0.0447	0.5943e-2	-213.0646	4.1155	4.1913
Total	-0.2153	0.0632	0.1812e-2	-208.1833	4.0225	4.0984

Sector Estimates

Sector	a_k	β_k	$S.E.\ \beta_k$	φ_k	σ_e^2	Log Likelihood
Consumer Products	-5.3192	-0.4322	0.1530	0.9279	0.05327	-138.1993
Energy	-5.6644	-0.1471	0.2406	0.8930	0.2717	-114.1767
Hotel, Gaming & Leisure	-4.7447	-0.3693	0.1797	0.8509	0.1477	-139.9052
Industrial	-5.3729	-0.6313	0.1081	0.9182	0.05315	-199.9158
Media	-5.2592	-0.5176	0.1695	0.5273	0.1929	-102.5362
Miscellaneous	-6.3232	-0.4881	0.3137	0.9582	0.08646	-52.4151
Retail	-4.9154	-0.3079	0.1544	-0.3493	0.4499	-122.4735
Technology	-5.4525	-0.1976	0.1562	0.9302	0.07059	-144.7543
Transportation	-5.2864	-0.5501	0.1647	0.4874	0.2101	-107.7024
Utilities	-7.5601	-0.0530	0.3263	0.9151	0.1761	-67.1619

Sector Estimates



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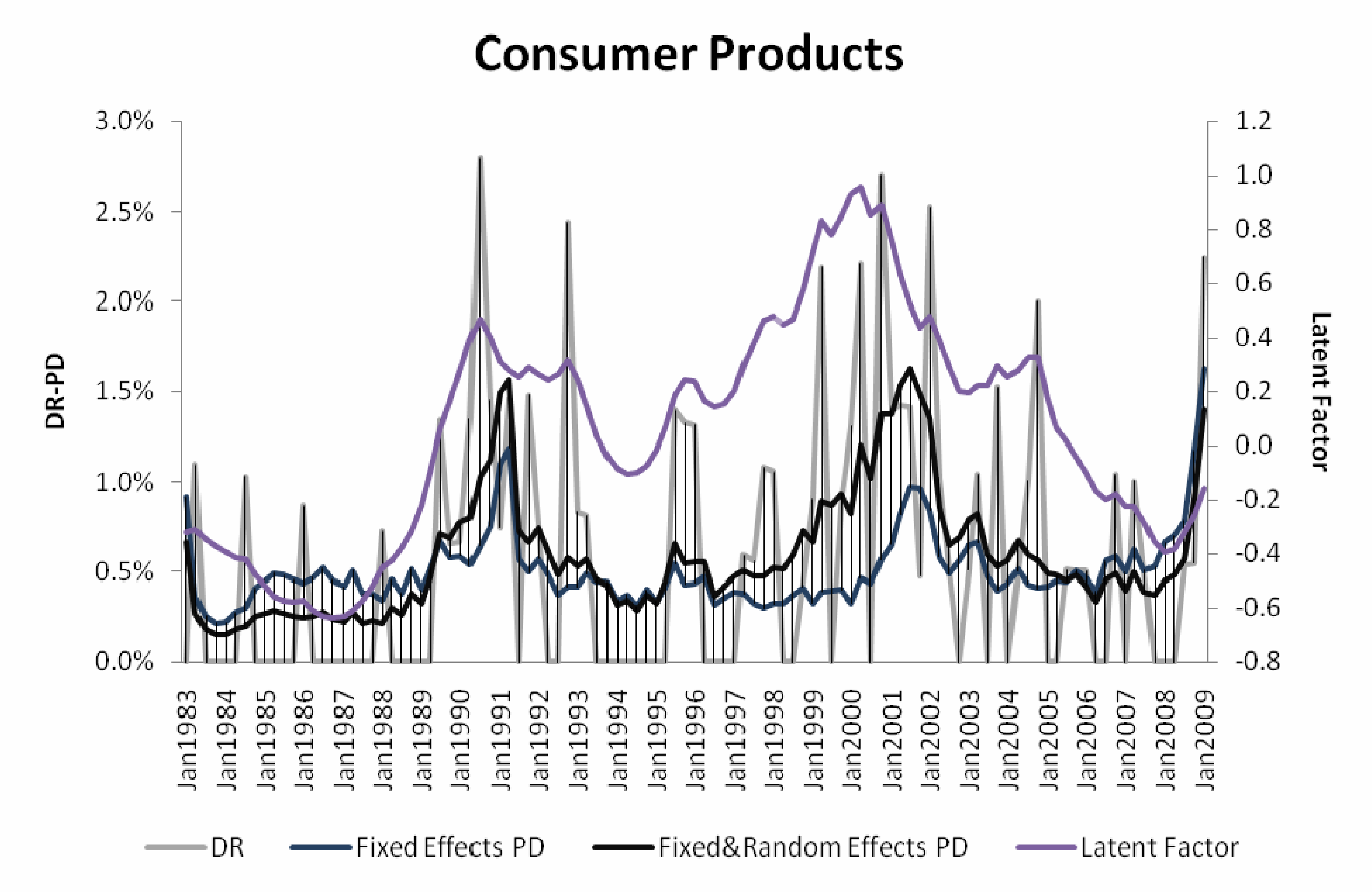

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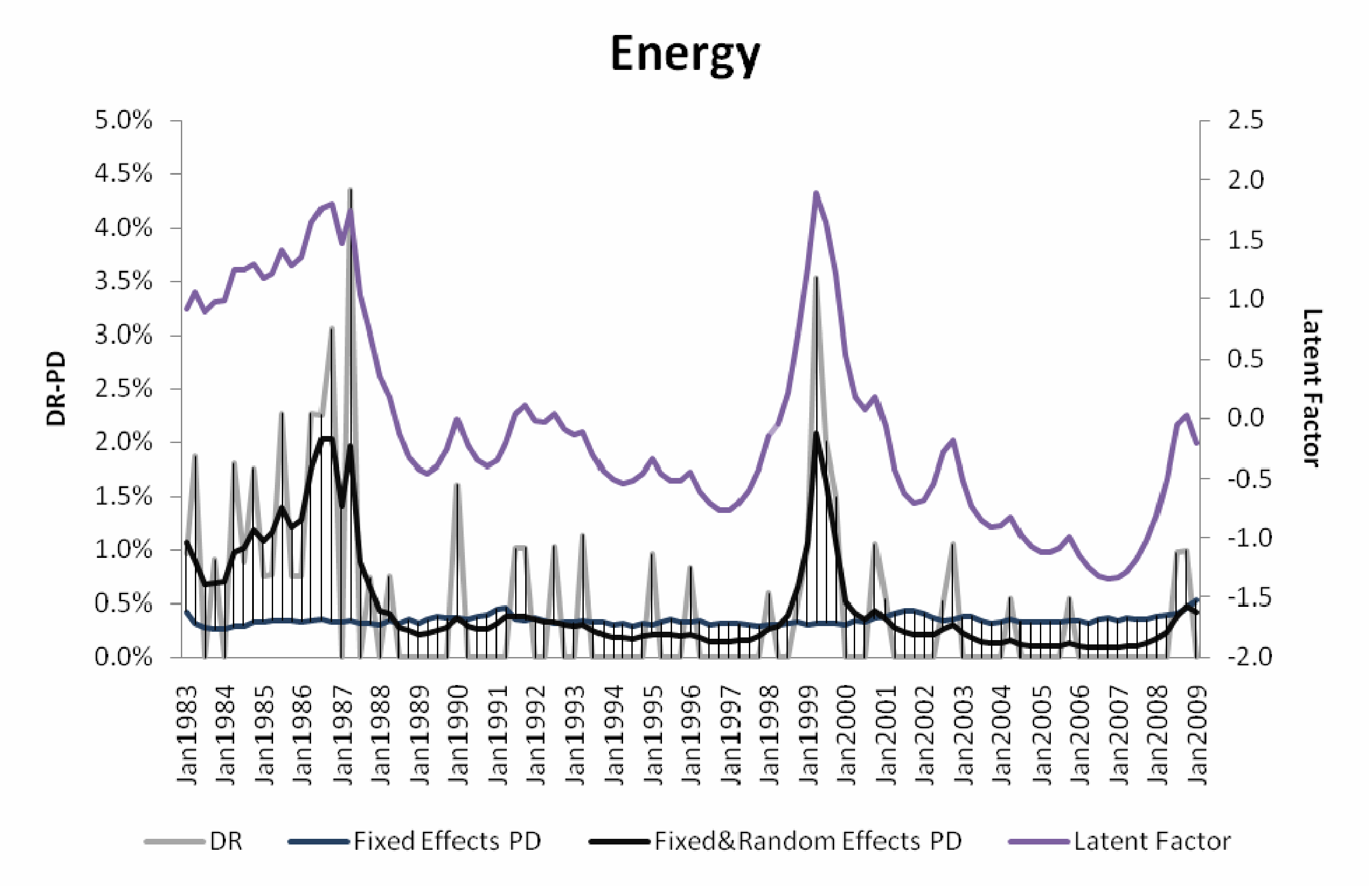

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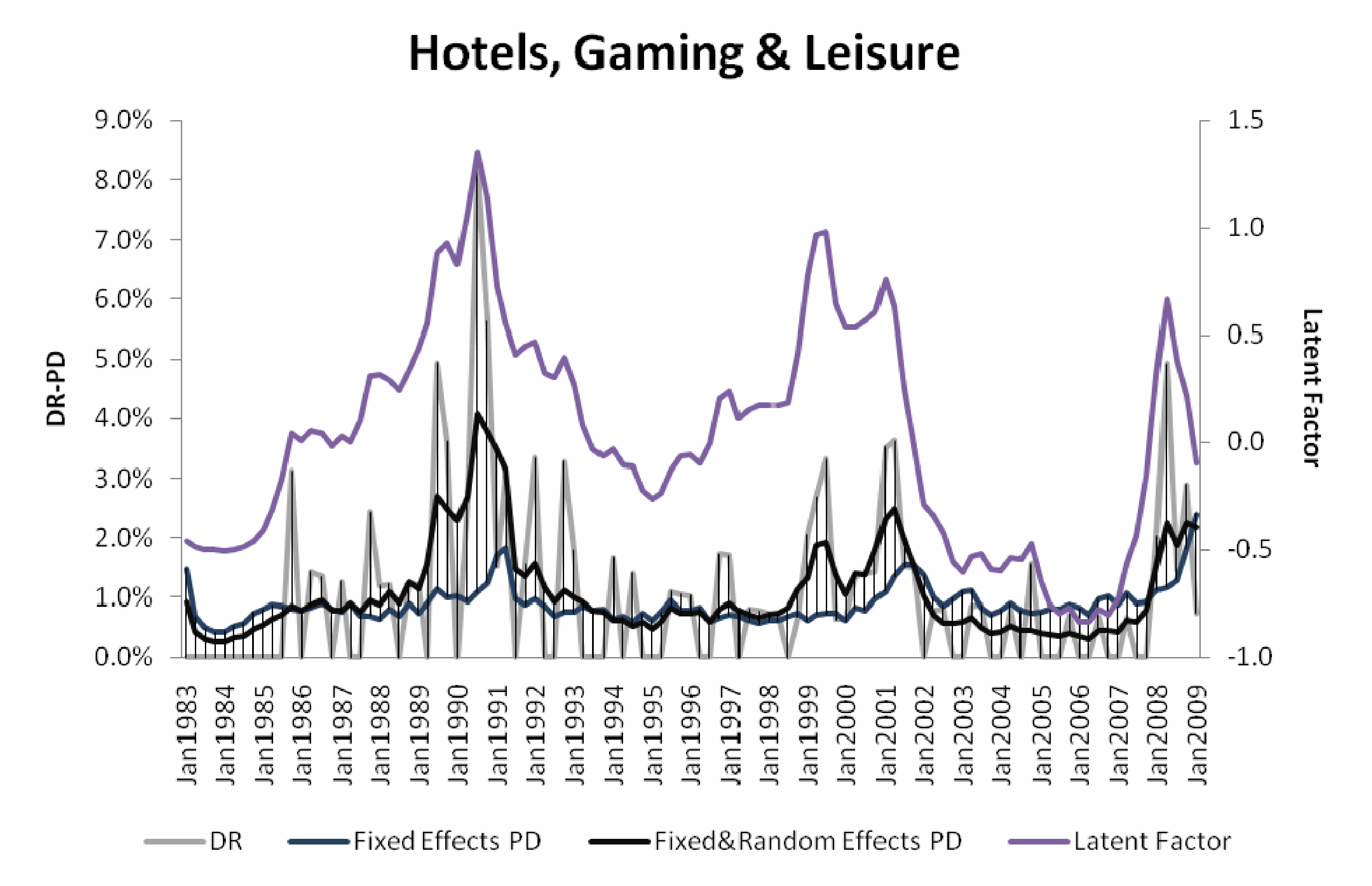

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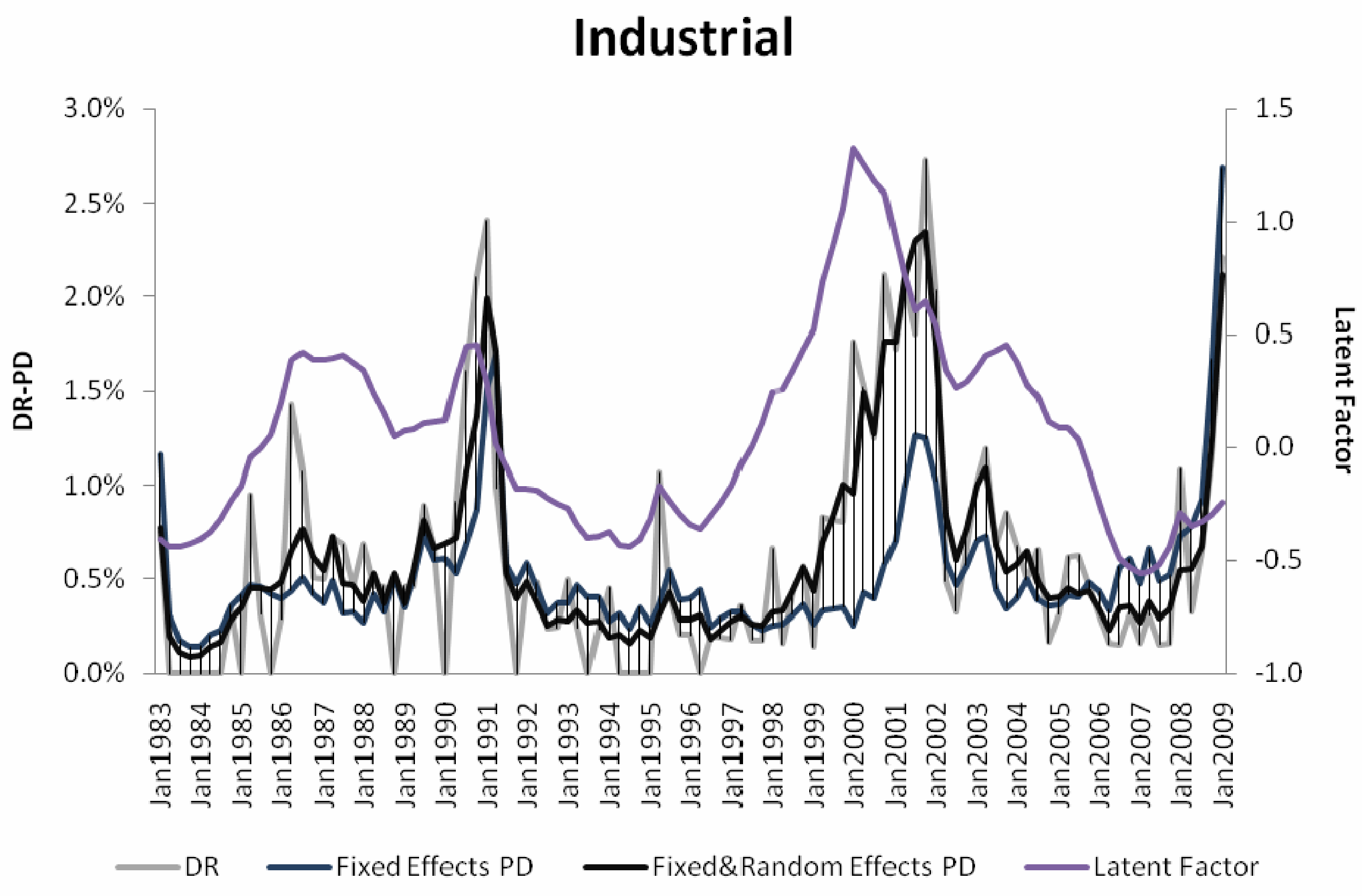

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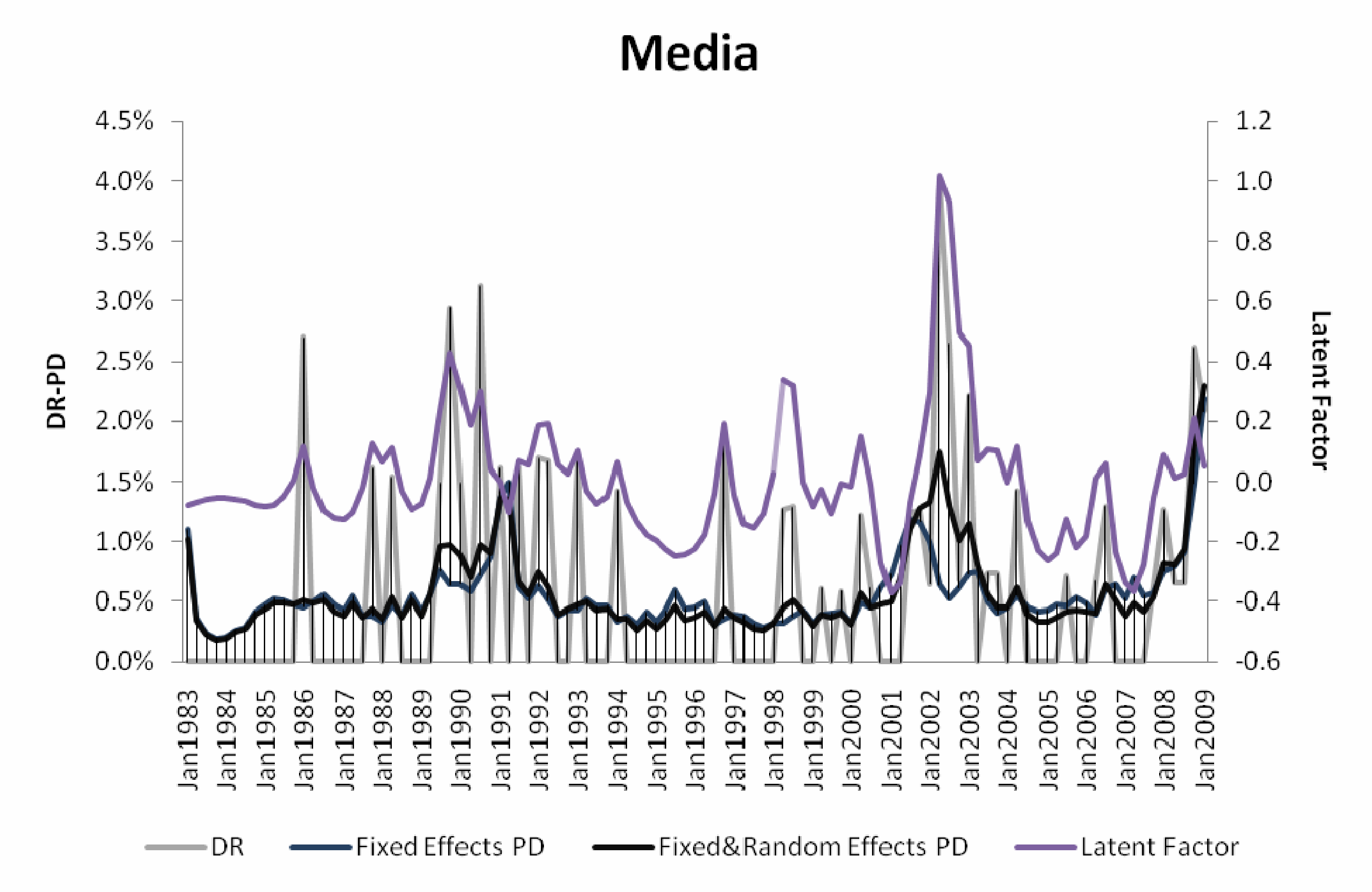

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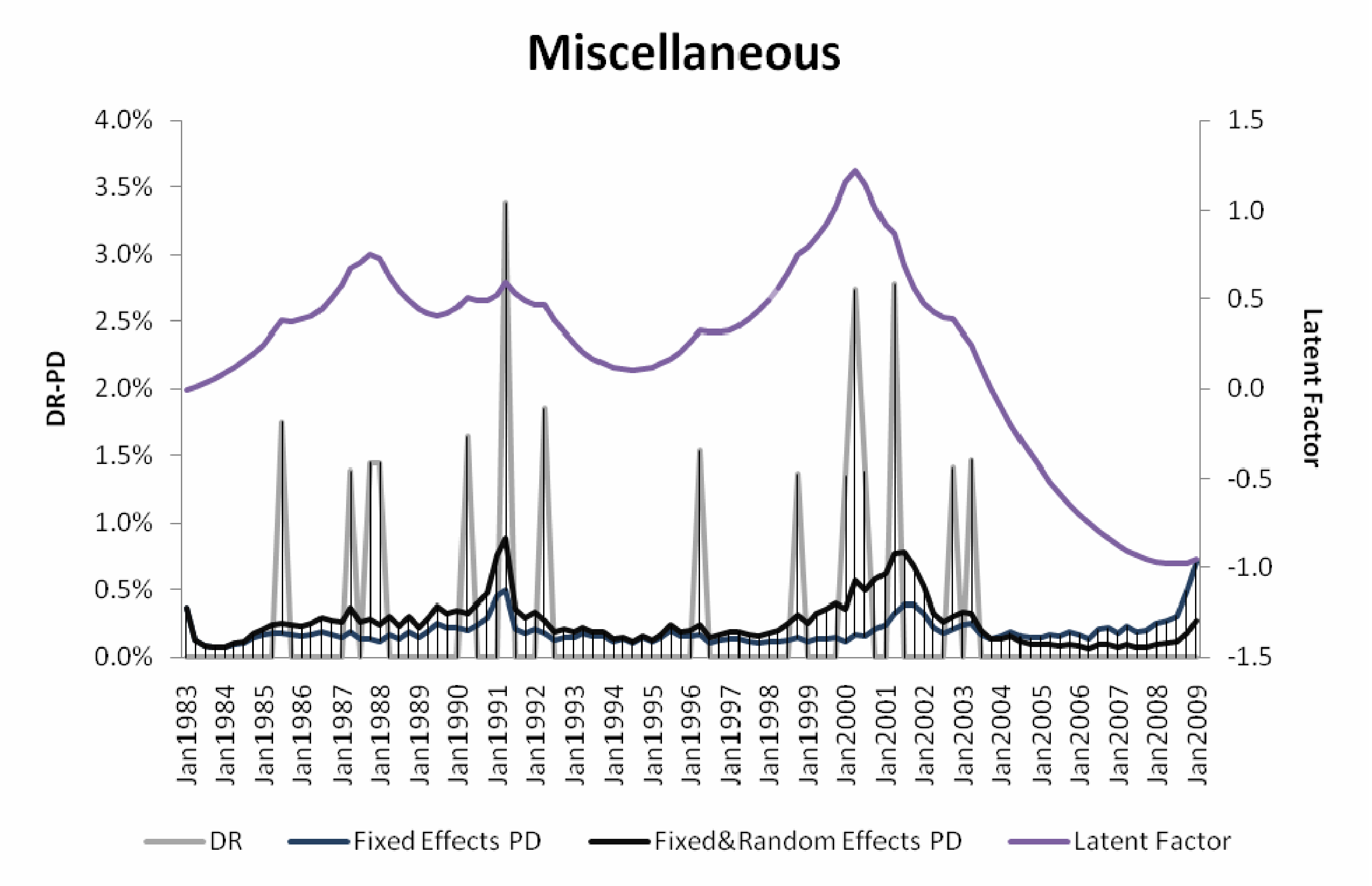

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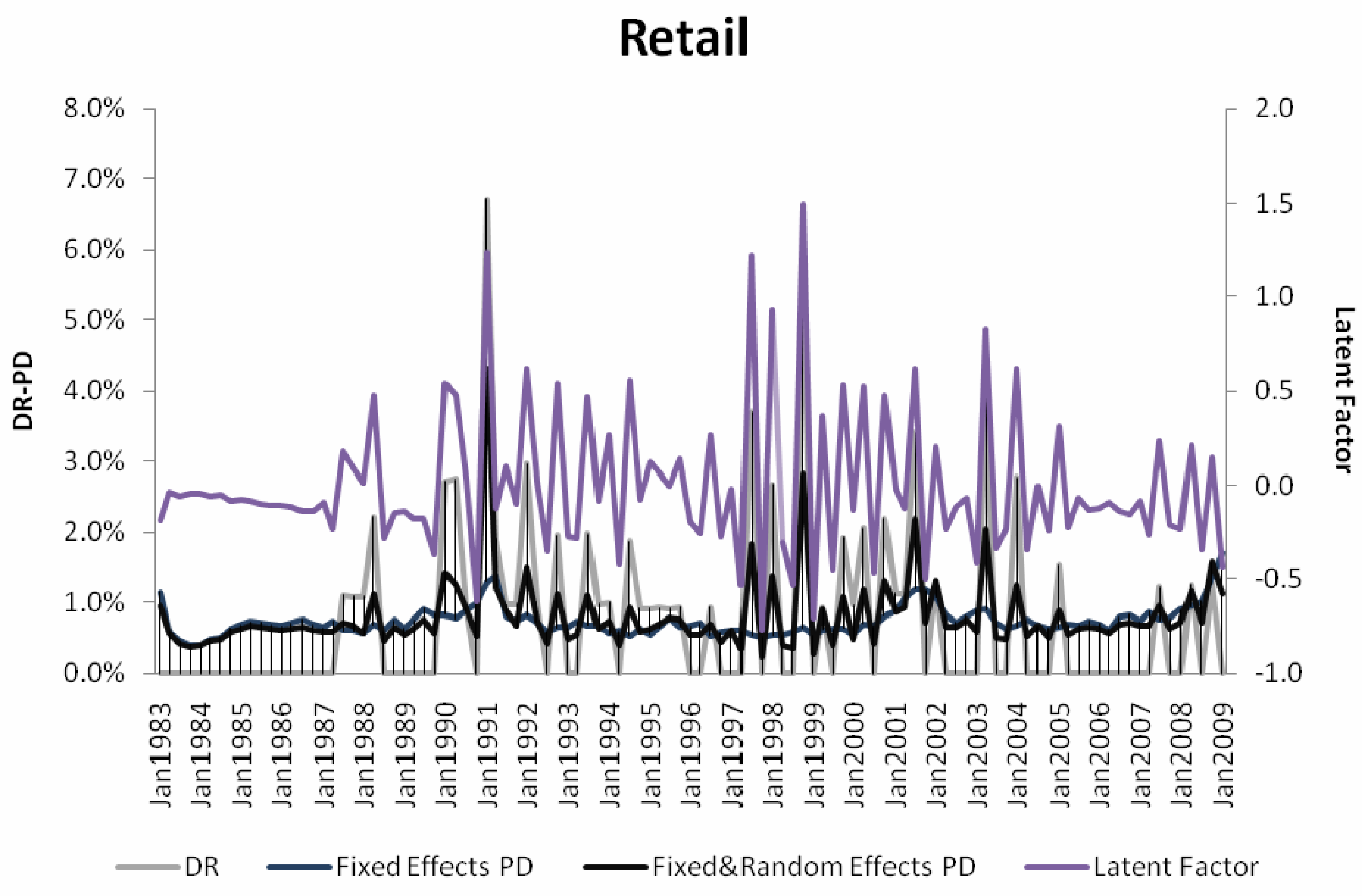

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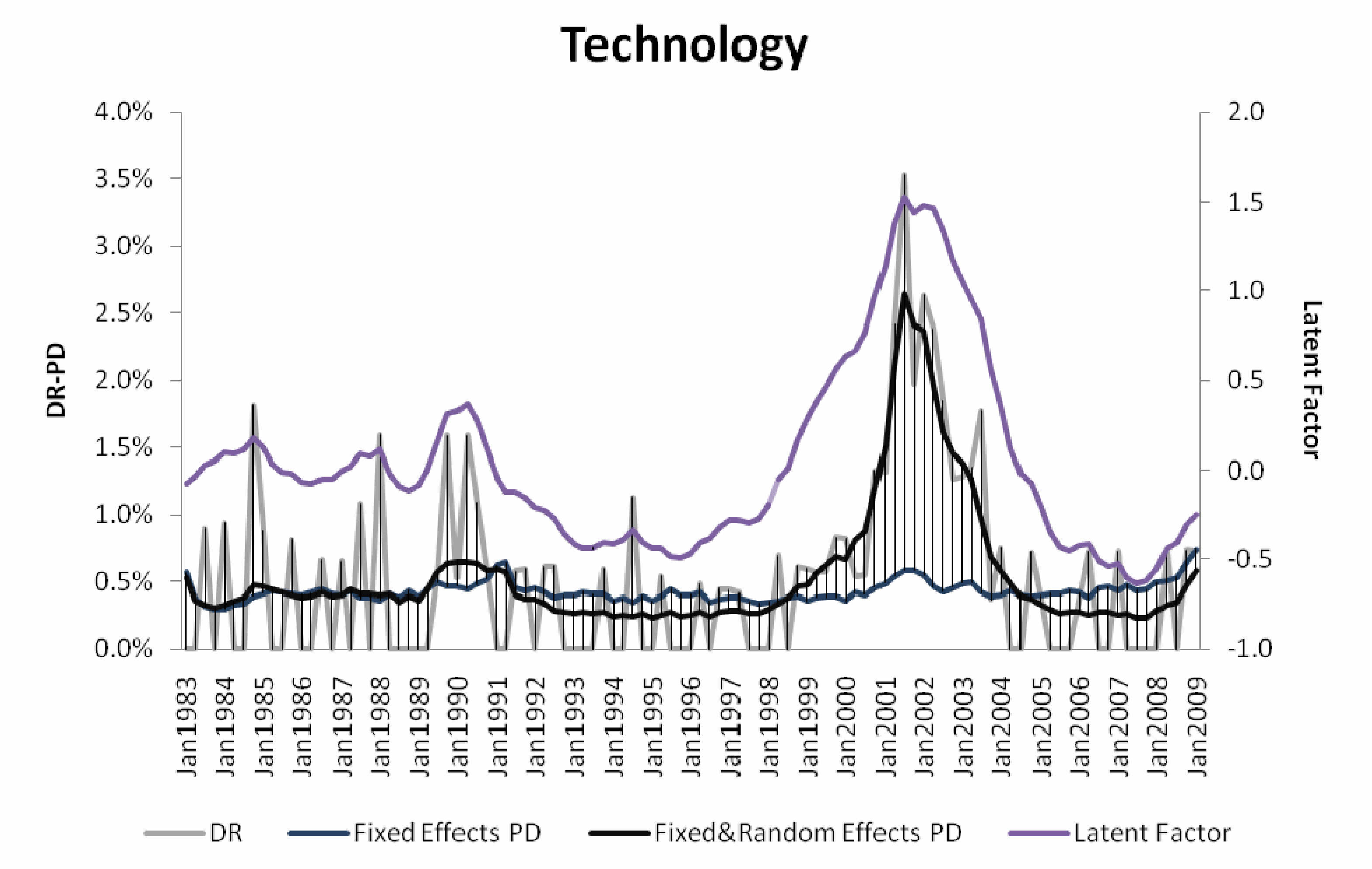

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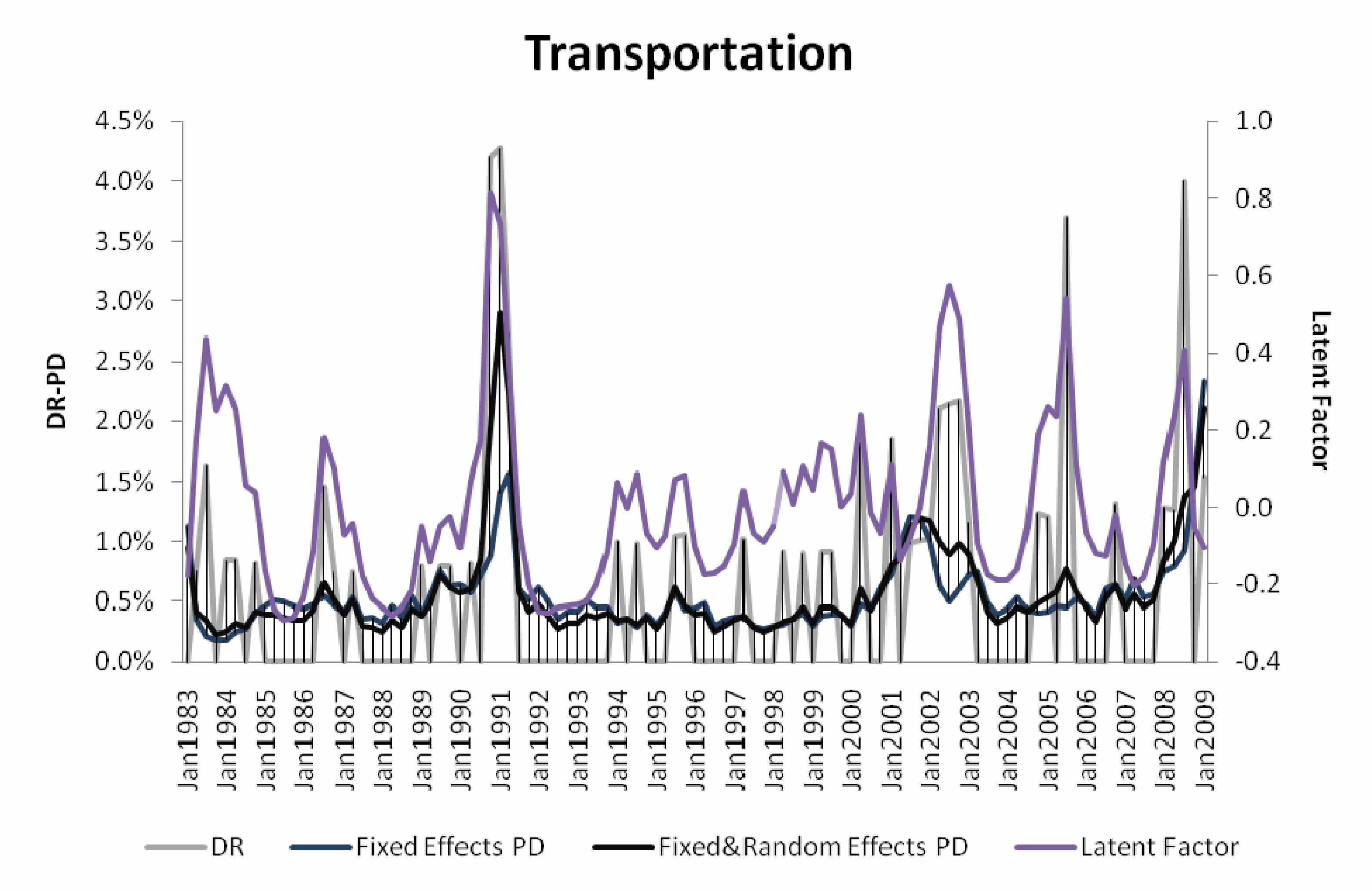

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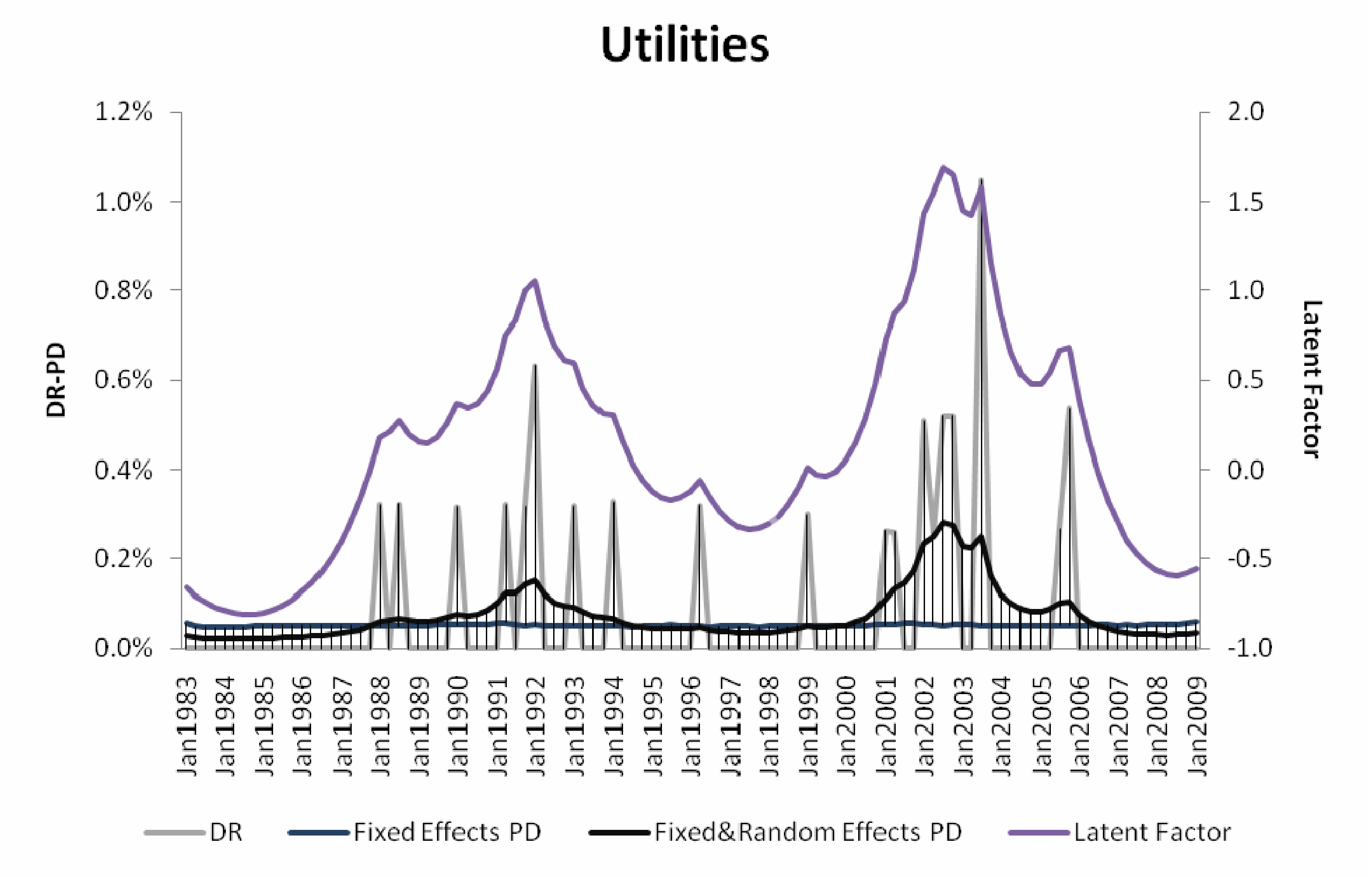

Result Summary

- Aggregate factor
  - Loads primarily from production
  - Primarily driven by output related factors, labour market conditions and wages
- Aggregate economy Credit Cycle
  - Labour market conditions show the best fit
  - Investment and cost of debt also seem to highly influence credit cycle
  - Aggregate macroeconomic factor highly significant, showing that the credit cycle is affected by the macroeconomic environment
- Sector credit cycles
  - Sector credit cycles are significantly different
  - Energy, Hotels, Gaming & Leisure, Retail, Technology and Utilities are not affected by the aggregated macroeconomic factor

Future Research

- Robustness of current model:
  - Assess the adequacy of the AR(1) specification for the dynamic factors and the autoregressive error terms
  - Assess the time stability of the macroeconomic factors coefficients into the latent factor regression against defaults
  - Ensure robustness of the DFM parameters using different estimation windows
  - Explore whether richer autoregressive structures for the latent variables improve fitting
  - Repeat DFM analysis with outliers removed
  - Test the forecasting power of the model
- Increase the number of dynamic factors for each subset
  - Identification issues
- More granular credit risk decomposition
  - Split by rating grade
- Extend the methodology to downgrades and upgrades