An Anatomy of Industry Merger Waves

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This paper ...

- We ask whether market transaction data are compatible with the idea that different theory-based factors determine heterogeneous wave-like patterns in the time series of same-industry deals flows.
- Our main result suggest this might be the case.
  - **Punchline:** Waves in different industries consistent with different (maybe competing) theories.

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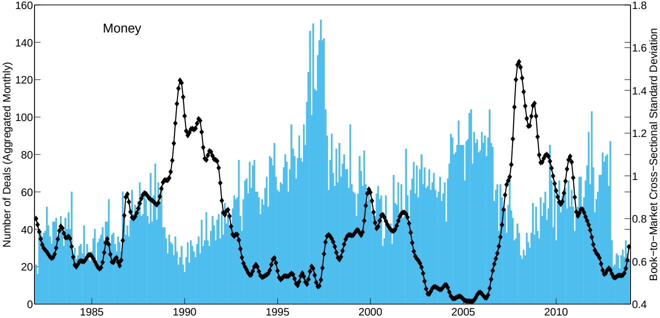

Figure: Industry-specific merger activity. This figure reports the time series of merger activity across industries (light-blue bars), measured as the number of all M&A bids announced by US private and public acquirers for US public and private targets in the period 1983:01 - 2014:12, monthly. Deals are measured as the number of all M&A bids announced by US private and public acquirers for US public and private targets. We considered those deals with a value higher than 5 $ Mil (including net debt of the target), and exclude those identified as spinoffs, re-capitalizations, self-tenders, exchange offers, and repurchases. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French. The black solid line with diamond markers shows the cross-sectional standard deviation of firms value-weighted book-to-market ratio. The left axis on each graph represent the number of deals, and the right axis show the scale for the explanatory variable.

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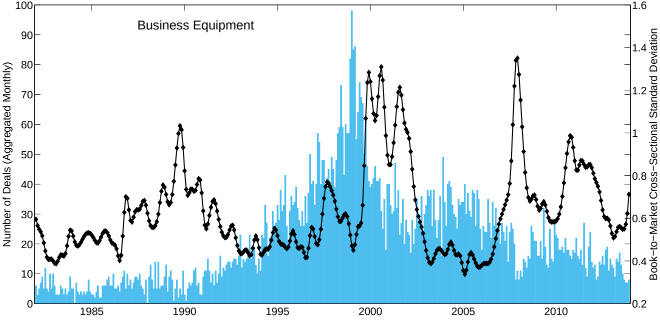

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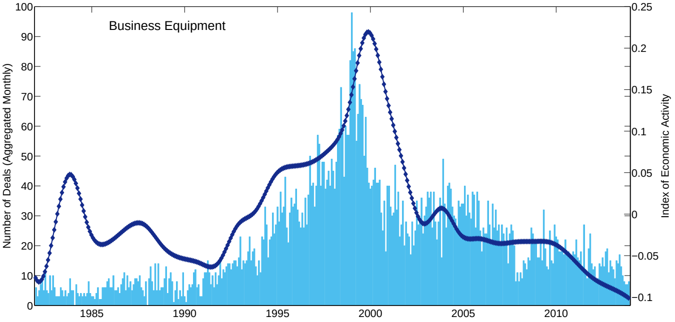

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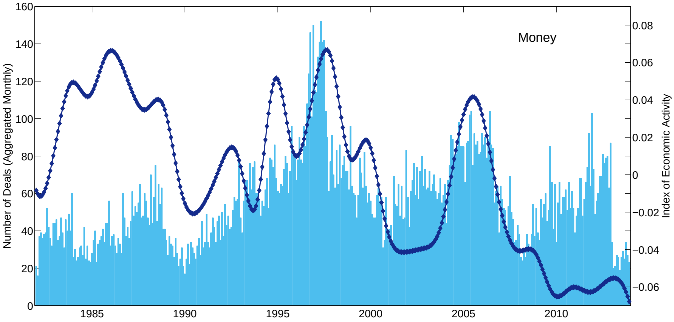

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From a **methodological** point of view:

- Propose a novel Markov regime-switching Poisson regression model with time-varying transition distributions to test theories of merger waves independently across industries.
- Our framework allows for regressors potentially endogenous in the dynamics of merger waves and non-Gaussianity in M&A activity
- Markov Chain Monte Carlo estimation approach

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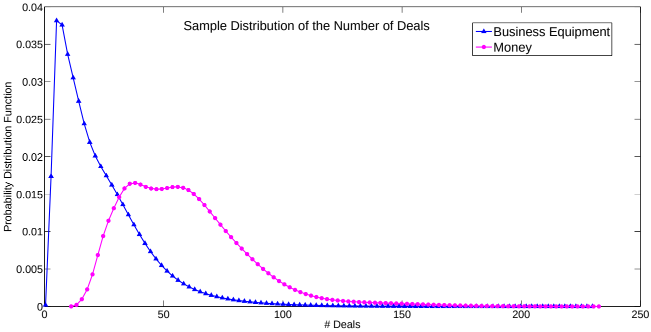

Figure: Sample distribution of M&A deals. This figure reports the empirical probability distribution function of M&A deals measured as the number of all M&A bids announced by US private and public acquirers for US public and private targets in the period 1983:01 - 2014:12, monthly. Deals are measured as the number of all M&A bids announced by US private and public acquirers for US public and private targets. We considered those deals with a value higher than 5 $ Mil (including net debt of the target), and exclude those identified as spinoffs, re-capitalizations, self-tenders, exchange offers, and repurchases. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French.

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From an **empirical** point of view:

- There is heterogeneity in the dynamics and persistence of merger waves across industries.
- Such heterogeneity is due to different exposures to competing theory-based factors.

Roadmap

- Related Literature
- Modeling Framework
- Empirical Analysis
- Conclusions

Related Literature

1. Identification of merger waves
   (e.g., Shugart and Tollison, 1984, Town, 1992 and Golbe and White, 1993, Harford 2005, Resende 2008, Maksimovic et al. 2013)
2. Behavioral hypothesis on merger waves
   (e.g., Shleifer and Vishny 2003, Rhodes-Kropf and Viswanathan 2004, Rhodes-Kropf et al. 2005, Maksimovic et al. 2013)
3. Neoclassical hypothesis on merger waves
   (e.g., Coase 1937, Harford 1999, Andrade et al. 2001, Maksimovic and Phillips 2001, Jovanovic and Rousseau 2002, Harford 2005)
4. Macroeconomic factors and merger waves
   (Melicher et al. 1993, Town 1992, Golbe and White 1993, Mulherin and Boone 2000)
5. MCMC Estimation strategy
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An Empirical Model of Same-Industry Merger Waves

Determinants	z^m_{t-1}	z^m_t	z^m_{t+1}
State of Merger Wave	S^m_{t-1}	S^m_t	S^m_{t+1}
Regression Parameter(s)	$\beta_{S^m_{t-1}}$	$\beta_{S^m_t}$	$\beta_{S^m_{t+1}}$
Utility to engage in M&A	$\boxed{U^m_{ij,t-1}}$	$\boxed{U^m_{ij,t}}$	$\boxed{U^m_{ij,t+1}}$
Individual attributes	$\epsilon_{ij,t-1}$	$\epsilon_{ij,t}$	$\epsilon_{ij,t+1}$
Time	$t-1$	t	$t+1$

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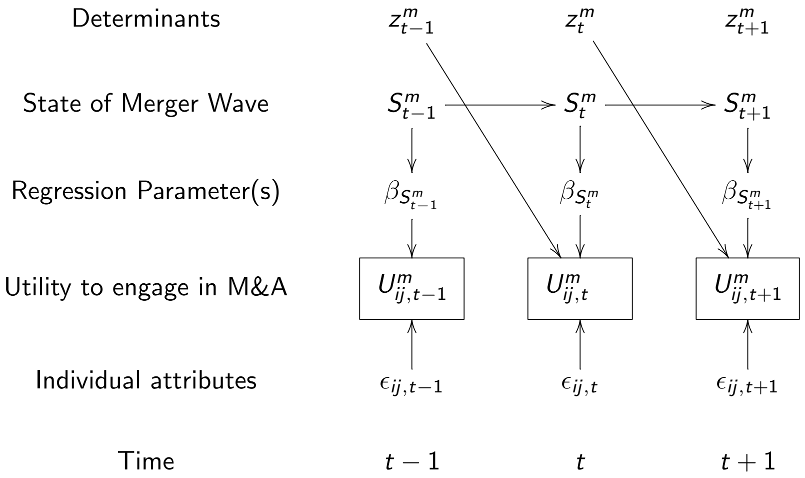

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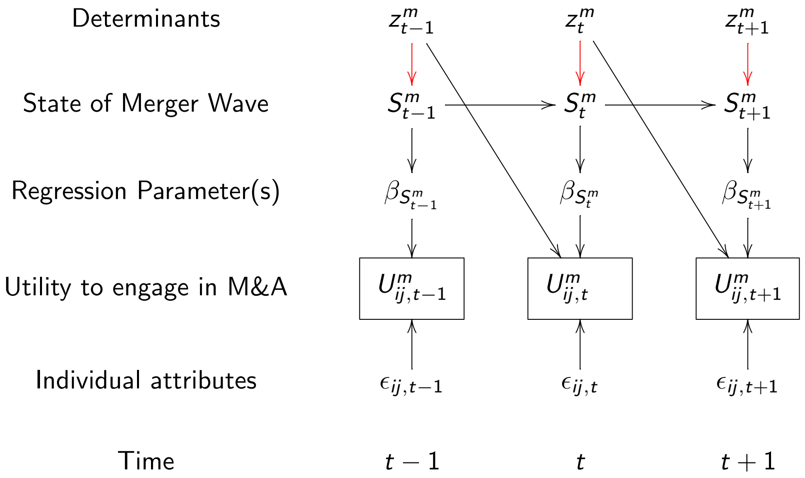

An Empirical Model of Same-Industry Merger Waves

Building block 1: Let $U^m_{ij,t} = z^m_{t-1}\beta^m_{S_t} + \epsilon_{ij,t}$ then

- The decision $j = 0$ is the benchmark, i.e. $U^m_{i0,t} = \epsilon^m_{i0,t}$;

$$M^m_{i,t} = 1 \qquad \text{if} \qquad z^m_{t-1}\beta^m_{S_t} + \epsilon_{i1,t} \geq \epsilon_{i0,t},$$

- If the *ith* bidder is utility maximizer (see, McFadden 1974)

$$\pi^m_{S_t,t} = Prob\left(M^m_{i,t} = 1\right) = \frac{\exp\left(z^m_{t-1}\beta^m_{S_t}\right)}{1 + \exp\left(z^m_{t-1}\beta^m_{S_t}\right)},$$

- For $y^m_t = \sum_{i=1}^{N} M^m_{i,t}$ at time t for the *mth* sector; parameters can be estimated through a Poisson model (see, Guimarães, Octavio, and Woodward 2003);

$$y^m_t|\lambda^m_{S_t,t} \sim Poisson\left(\lambda^m_{S_t,t}\right) \qquad \lambda^m_{S_t,t} = \exp\left(z^m_{t-1}\beta^m_{S_t}\right)$$

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Building block 2: Time-varying transition probabilities

- Transitions towards merger waves are affected by two components:
  - A time varying component $z_t^m \alpha^z_{S t-1, S_t}$ (effect of the determinants on switching probabilities);
  - A time-invariant component α_{S_{t-1}, S_t} (state persistence);

$$p\left(S_t = k | S_{t-1} = l, z_t^m, \alpha\right) = \xi_{lk,t} = \frac{\exp\left(z_t^m \alpha^z_{lk} + \alpha_{lk}\right)}{\sum_{j=1}^{K} \exp\left(z_t^m \alpha^z_{lj} + \alpha_{lj}\right)},$$

with $\alpha' = \left(\alpha^{z,\prime}_{S_{t-1}, S_t}, \alpha'_{S_{t-1}, S_t}\right)$ an $(N + K)-$dimensional vector of parameters.

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Empirical Analysis: Data

- **Deals:** The sample includes 60,305 bids for US private and public acquires that were announced in the period from 1983 to 2014.
  - A deal is included after some filter, e.g. transaction value is above $5 million. Deals are aggregated monthly at the industry level (four-digit SIC code of the bidder)
- **Economic Activity:** Following Harford (2005); an industry-specific economic activity index computed as the first principal component from seven variables (margin on sales, AT, R&D, CAPX, employee growth, ROA, and sales growth).
- **Valuation Variables:** Industry-specific average book-to-market ratio, its cross sectional standard deviation and the value-weighted industry stock returns.
- **Macro-financial factors:** Industrial production growth (year-on-year), the credit spread, the real risk free rate and a measure of capital liquidity.

Digression: Cubic Spline Interpolation

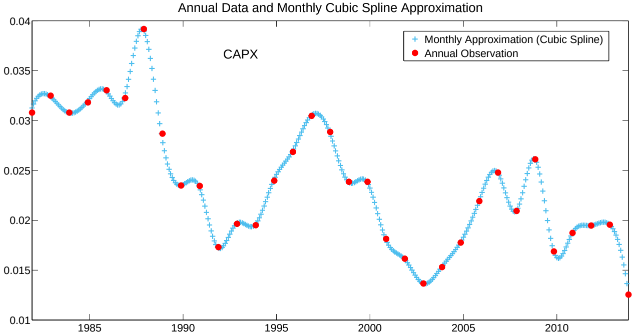

Figure: This figure shows the actual annual observation of the data on industry specific economic shocks and the monthly approximation obtained by a cubic spline interpolation method. The interpolation method has the advantage of producing a smooth implied decision process, which is more consistent with our random utility model, and, in particular, avoids jumps in the implied intensity rate resulting from impounding the entire change in merger activity to one day at the end of each period. The sample period is 1983-2014.

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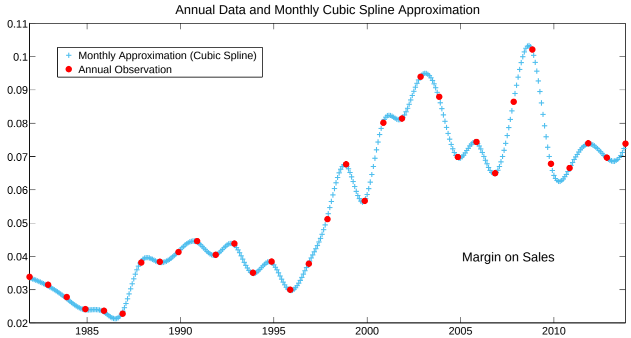

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Empirical Analysis: Estimation algorithm

- We use Markov chain Monte Carlo (MCMC) techniques to explore the posterior distribution for both parameters and latent state of merger waves;
- For a given state $S_t = k$, with $k = 1, \dots, K$, the prior structure is conjugate;
- The practical implementation for non-linear models such as ours requires the use of a Metropolis-Hastings steps to estimate the parameters vector.
- We propose an approximate, yet accurate, Gibbs sampling scheme for both the unknown parameters and the hidden states of merger activity (see, e.g. Frühwirth-Schnatter and Wagner 2006 and Kaufmann 2015).
  - Introduce two sequences of auxiliary latent variables through data augmentation to sample the parameters of the Poisson regression and the transition distributions;

What Drives Merger Waves?

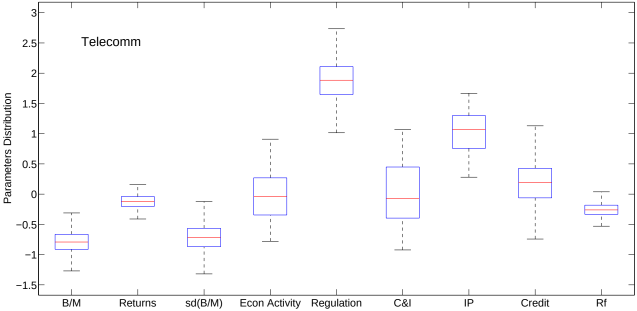

Figure: This figure shows the effect of explanatory variables on the posterior probability of a merger wave as identified by the $N-$dimensional vector of coefficients $\alpha_{12}^{z} = \left(\alpha_{12,1}^{z}, \cdots, \alpha_{12,N}^{z}\right)$. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French. The set of explanatory variables is determined by industry-specific book-to-market ratio B/M, its cross-sectional standard deviation $sd(B/M)$, past cumulated returns (*Ret*), an index of economic activity computed as the first principal component of a collection of industry-specific economic shocks (*Econ Activity*), capital liquidity conditions (proxied by the spread between the average interest rate on commercial and industrial loans and the Federal Funds rate, $C\&I$), the monthly compounded year-on-year industrial production growth (*IP*), the yield spread between 20-year Baa and Aaa corporate bonds (*Credit*), and the difference between the 1-month T-Bill rate and monthly inflation rate (*Rf*). The sample period is 1983:01-2014:12, monthly.

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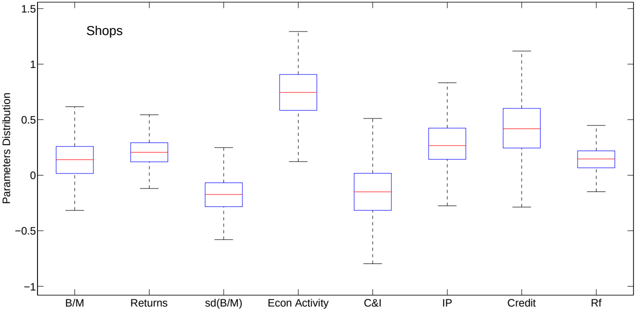

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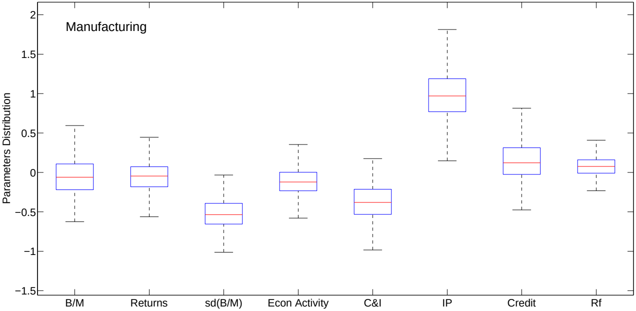

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What Drives Merger Waves?

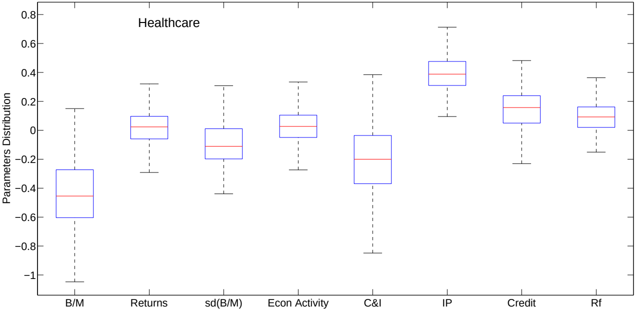

Figure: This figure shows the effect of explanatory variables on the posterior probability of a merger wave as identified by the $N-$dimensional vector of coefficients $\alpha^z_{12} = \left(\alpha^z_{12,1}, \cdots, \alpha^z_{12,N}\right)$. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French. The set of explanatory variables is determined by industry-specific book-to-market ratio B/M, its cross-sectional standard deviation $sd(B/M)$, past cumulated returns (*Ret*), an index of economic activity computed as the first principal component of a collection of industry-specific economic shocks (*Econ Activity*), capital liquidity conditions (proxied by the spread between the average interest rate on commercial and industrial loans and the Federal Funds rate, $C\&I$), the monthly compounded year-on-year industrial production growth (*IP*), the yield spread between 20-year Baa and Aaa corporate bonds (*Credit*), and the difference between the 1-month T-Bill rate and monthly inflation rate (*Rf*). The sample period is 1983:01-2014:12, monthly.

Posterior Probabilities of Merger Waves

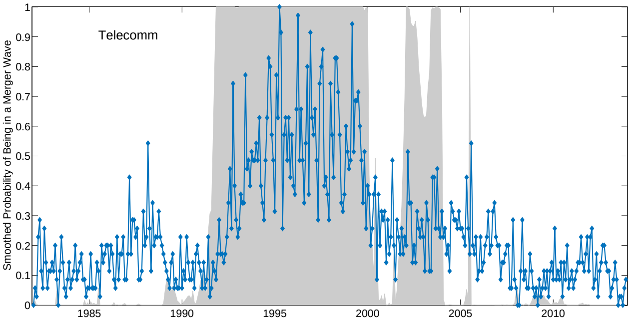

Figure: Posterior probability of being in a merger wave at each time t. This figure shows the model-implied probability of being in a state of abnormally high merger activity. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French. The solid blue line with diamond markers shows the rescaled number of deals for each industry. The sample period is 1983:01-2014:12, monthly.

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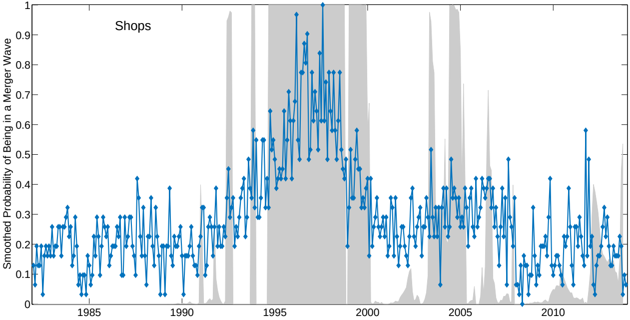

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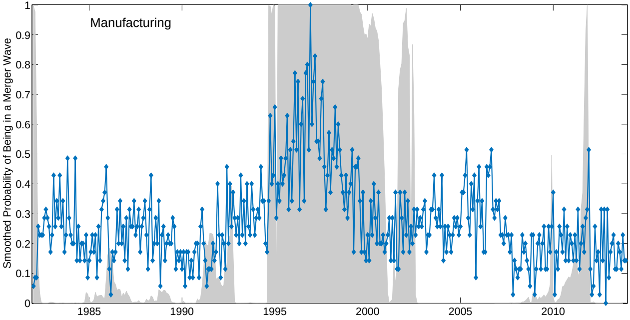

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Synchrony of Wave Probabilities

- Merger waves are not necessarily overlapping across industries over time.
- We test the degree of synchrony of wave probabilities by computing a pairwise coincidence rate.
- We construct a state indicator;

$$\mathbb{I}_{\{S_t^m=1\}} = \begin{cases} 1 \quad \text{if} & p\left(S_t^m = 1 | \mathbf{y}_{1:t}^m, \mathbf{z}_{1:t}^m\right) \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$$

- Then we construct our coincidence measure between industry i and j, by simply counting in-sample how many times the indicator gives the same signal

$$\text{CoinRate}_{ij} = \frac{1}{T} \sum_{t=1}^{T} \mathbb{I}_{\{S_t^i = S_t^j\}} \in [0, 1],$$

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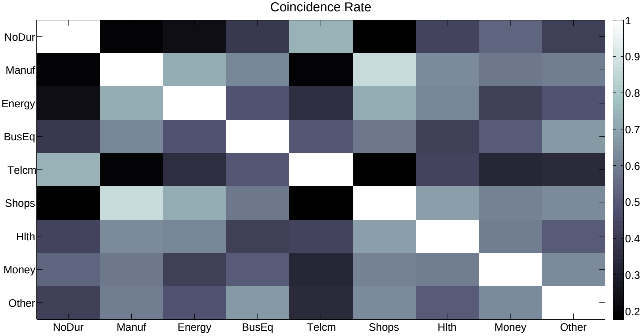

Figure: Cross-industry correlation of merger waves. This figure shows the in-sample pairwise coincidence rates of merger waves indicators between industries. We construct an indicator that takes value one if the model-implied waves indicate the same outcome for both industries (either wave or absence of wave) and zero otherwise. The heating maps report the probability of observing the same outcome. The sample period is 1983:01-2014:12, monthly. Estimates of the model-implied waves are based on posterior medians obtained from the Gibbs sampler detailed in Appendix A. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French.

Model Assessment: Testing Regimes - Marginal Likelihood

	Marginal Likelihoods								
	NoDur	Manuf	Enrgy	BusEq	Telcm	Shops	Hlth	Money	Other
$K = 1$	-237.39	-178.21	-211.68	-690.83	-209.10	-238.75	-516.75	-407.07	-609.06
$K = 2$	-106.92	-118.54	-54.24	-187.72	-134.84	-138.22	-201.04	-200.32	-303.48
$K = 3$	-244.39	-272.25	-115.73	-676.76	-141.26	-141.01	-210.32	-311.39	-536.46
$\log_{10} \mathcal{B}_{2,1}$	56.66	25.91	68.37	218.49	32.25	43.66	137.10	89.79	132.71
$\log_{10} \mathcal{B}_{2,3}$	59.70	66.75	26.70	212.38	2.787	1.214	4.026	48.23	101.18

Table: This table reports the results of a formal test for the number of regimes for each specification of regressors and across industries. We report the marginal likelihoods and the corresponding Bayes factor in $\log_1 0$-scale comparing the model with tw regimes, i.e. $K = 2$ against a standard Poisson regression, i.e. $K = 3$, and a model with three regimes, i.e. $K = 3$. Bayes factors are based on marginal likelihoods (see Kass and Raftery 1995). The sample period is 1983:01-2014:12, monthly.

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Model Assessment: Testing Regimes - Prediction

Forecasting Horizon, $h = 6$									
	NoDur	Manuf	Enrgy	BusEq	Telcm	Shops	Hlth	Money	Other
	RMSE								
$K = 1$	9.470	24.06	21.44	80.16	45.46	18.48	36.39	165.5	126.0
$K = 2$	6.580	7.334	10.45	12.26	17.39	4.331	22.35	119.3	24.14
$K = 3$	7.238	14.42	12.61	28.39	19.12	8.988	28.68	125.1	81.36
	Log-Predictive Score								
$K = 1$	-20.81	-38.96	-15.40	-82.71	-24.97	-22.22	-38.76	-174.7	-90.77
$K = 2$	-16.09	-17.77	-10.15	-18.47	-14.90	-15.21	-25.25	-44.83	-22.20
$K = 3$	-17.69	-24.91	-12.45	-26.08	-13.04	-21.55	-31.22	-43.50	-51.44

Table: This table reports two different performance measures to assess the predictive power of our Markov regime switching Poisson regression model with time-varying transition probabilities for different forecasting horizons and alternative model specifications, i.e. $K = 1, 2, 3$ regimes. We show the standard Root Mean Squared Errors (RMSE) and the Log Predictive Score, both computed sampling from the predictive density of the model obtained integrating out uncertainty on both parameters and latent states. Panel B shows the same performance metrics for $h = 6$. The sample period is 1983:01-2014:12, monthly.

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Model Assessment: Intensity Rates

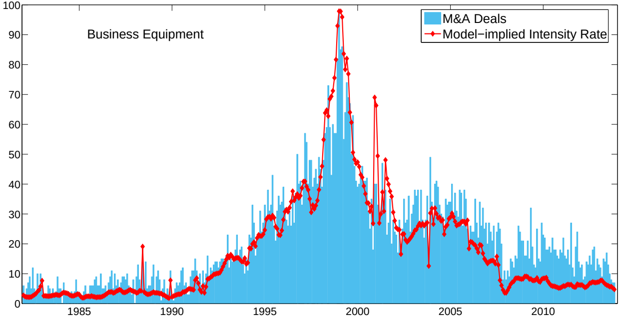

Figure: This figure shows the actual number of M&A deals and the median model-implied intensity rates computed assuming there two distinct regimes identifying merger waves, i.e. $K = 2$. Deals are measured as the number of all M&A bids announced by US private and public acquirers for US public and private targets in the period 1983:01 - 2014:12, monthly. We considered those deals with a value higher than 5 $ Mil (including net debt of the target), and exclude those identified as spinoffs, re-capitalizations, self-tenders, exchange offers, and repurchases. Industry classification is based on the four-digit SIC codes according to the twelve-industry classification provided by Kenneth French. The solid red line is the merger intensity rate implied by the model. The sample period is 1983:01-2014:12, monthly.

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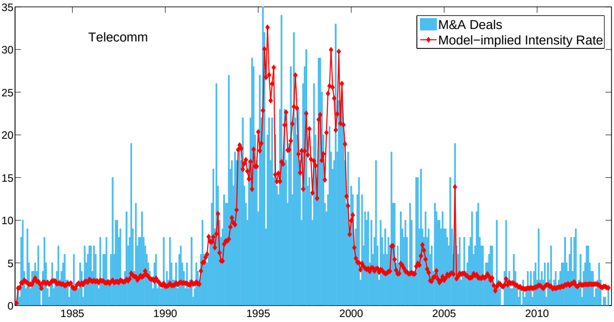

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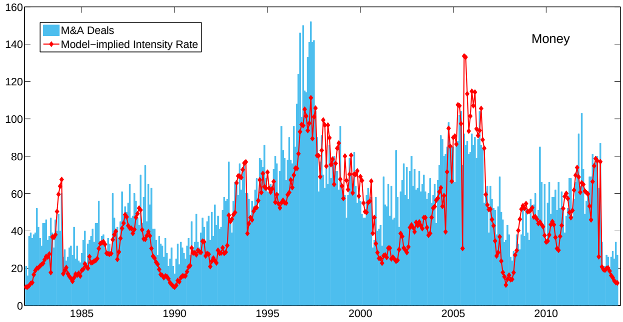

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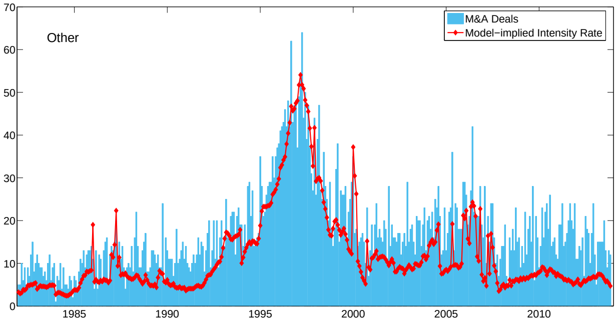

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Conclusions

- **Methodologically**, we propose a Markov regime-switching Poisson regression model with time-varying transition distributions to rationalize wave-like patterns in the intensity rate of industry-specific merger activity.
  - Efficient MCMC estimation algorithm
- **Empirically**, we show that merger waves varies significantly across industries, both in terms of timing/persistence and determinants.
  - Aggregating deals at the market level could be misleading