Intersectoral default contagion: A multivariate Poisson autoregression analysis

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Abstract

This paper analyzes credit rating default dependencies in a multisectoral framework. Using Mergent's FISD database, we study the default series in the U.S. over the last two decades, disaggregating defaults by industry-sector group. During this period, two main waves of default occurred: the implosion of the "dot-com" bubble and the global financial crisis. We estimate a Multivariate Autoregressive Conditional Poisson model according to the biweekly number of defaults that occurred in different sectors of the economy from 1996 to 2015. We discuss the contagion effect between sectors in two ways: the degree of transmission of the probability of default from one sector to another, i.e., the "infectivity" of the sector, and the degree of contagion of one sector from another, i.e., the "vulnerability" of the sector. Our results show differences between the sectors' relations during the first and second part of our sample. We add some exogenous variables to the analysis and evaluate their contribution to the goodness of fit.

JEL classification: C52, C61, G32, G33.

Keywords: Default contagion, Financial crises, Poisson autoregressive process, Intensity estimation.

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1 Introduction

It has been widely documented, particularly in Moody's reports on default rates (see, for example, Berthault et al., 2000), that the number of firm defaults is highly correlated with the economic business cycle and with the industry-sector-specific evolution. The corporate bond market has repeatedly suffered from the clustering of default events to a much greater extent than during the period of the Great Depression (see Giesecke et al., 2011).

The clustering of defaults could be explained by common factors that affect the default risk of individual firms (see Das et al., 2006). It could be due to internal problems that arise when firms are unable to generate cash flow in a distressed scenario – mainly because of disruptions in demand, supply, commodity prices, and/or production costs. This kind of default dependence or *conditional dependence* is cyclical, as it is related to the economic cycle and other macrostructure factors (see Giesecke and Weber, 2006). In a highly interrelated economy, the ability of firms to generate cash flows and hence their propensity to default vary with the fundamentals of the economy, such as commodity prices, asset demand and production costs. The relationship of firms with the general economic environment could induce dependence between firms' defaults (Giesecke and Weber, 2004).

There is another type of default dependence, *credit contagion*, that is related to business relationships or legal interdependencies that can exist between companies.[1] The most common kind of direct links between companies are those that involve productive processes that are necessarily related, for example, the assembly of cars and the production of tires for vehicles, as well as borrowing and lending contracts or other legal links, such as parent-subsidiary relationships.[2] Credit contagion risk is thus the risk that is due to microstructural factors such as business relationships or legal interdependencies. It seems unavoidable that in the presence of these types of company links, the cash flow generation problems of one company could entail an increase in their propensity to default and, hence, the propagation of the default probability from one firm to another. Lando and Nielsen (2010) address what they refer to as the "domino effect" to explain the clustering of defaults, as long as there are occasional default events that are not considered the result of contagion but are, on the contrary, a clear case of contagion.

All of these prior factors could cause firm defaults to cluster over time depending on the economic business cycle, variations in common macrostruc-

[1] In most cases, these direct company links occur within a specific sector, for example, the direct links among firms belonging to the banking sector, but are not necessarily always produced within one industry group. Along these lines, Lang and Stulz (1992) show that bankruptcy announcements strongly decrease the value of a portfolio of competitor stocks.

[2] See, for example, Emery and Cantor (2005), a study that finds that approximately 80% of companies suffer a default when an affiliate defaults.

ture factors and/or specific microstructural interdependencies. In this paper, we study the credit contagion risk that could be underlying microstructural dependence, controlling for the conditional dependence that could exist due to macroeconomic factors. We analyze the role of credit contagion in two directions that we call "vulnerability" and "infectivity". We define vulnerability as the transmission effect that affects firms from one sector and that has been generated in firms from another sector. In this case, one sector is affected by credit problems that arise first in another sector. Conversely, we define infectivity as the credit risk transmission effect that starts in companies operating in one sector and that ends up affecting firms belonging to another industry group. In this situation, credit problems in one sector trigger credit deterioration in firms from other sectors.

Several recent papers have found evidence in favor of the relationship between defaults and macroeconomic variables (see, for example, Chen and Wu, 2014; Yurdakul, 2014). Moreover, there is ample evidence that firm defaults are correlated and tend to cluster over time. Since the paper by Das et al. (2007), who analyze the sources of default clustering on U.S. industrial and financial firm defaults, many studies have analyzed this issue and developed new models, finding evidence of the existence of correlation between corporate defaults.[3] Egloff et al. (2007) propose a model of credit contagion that includes macro- and microstructural interdependencies among the debtors of a credit portfolio. They find that both interdependencies, particularly microstructural ones, seem to explain the tail behavior of portfolio credit losses, suggesting that both channels should be included in the modeling of credit contagion. Dong and Wang (2014) implement a model where the intensities are all affected by macroeconomic conditions and the interdependent default structure arises from default contagion, allowing them to capture the default clustering phenomenon. Their model provides flexibility in incorporating the impacts of changes in macroeconomic factors and default contagion into the default intensities.

In a more recent work, Lando and Nielsen (2010) analyze the sources of correlation in corporate defaults. The authors review the paper by Das et al. (2007) and perform different analyses to test for conditional independence or contagion effects among U.S. industrial firm defaults. They use a different specification of the default intensity, which provides different results than those in Das et al. (2007), since they cannot reject the same tests as in the previous results. In this last work, the contagion effect through "covariates", which are an indicator of the default intensities of firms, cannot be detected with their specification of default intensity, which Lando and Nielsen (2010) suggest is a problem of misspecification. To check this, they implement a new

[3] Other indirect evidence that corporate defaults are correlated can be found in, for example, Collin-Dufresne et al. (2001), who finds evidence of common movements in corporate bond spreads, and Collin-Dufresne et al. (2010), who finds empirical support for contagion in bond returns in response to large credit events.

test using the Hawkes process alternative to analyze whether microstructural dependencies among U.S. industrial firms are affected by the occurrence of defaults, concluding that there is no evidence of the existence of a channel of default contagion. Using another kind of model, Agosto et al. (2016) find evidence that macroeconomic factors are able to explain the observed firm default correlation in U.S. industrial firms. Azizpour et al. (2018) study the different sources of default clustering on U.S. firms. They find that contagion is the main factor in explaining default clustering and that only a residual and insignificant amount is unexplained by this source.

The vast majority of large companies have some kind of debt issues among their funding sources. Additionally, the debt of almost all major companies has been rated at least by one credit rating agency (CRA). It is a fact that when a firm experiences economic problems, its debt reflects this issue, showing low ratings for issuer creditworthiness. In fact, bond firm defaults should sometimes precede and anticipate the firm default itself.[4] Therefore, these rating categories should be an indicator of, in the best case, transitory problems or, in the worst case, structural problems. This fact could be relevant for other firms with tie-in businesses, as long as one firm default could increase the probability of default of another firm or even trigger the other firm's default. This paper analyzes credit rating default dependencies in a multisectoral framework in the U.S. corporate bond market. We study default clustering over the period starting in April 1989 and ending in April 2015, disaggregating defaults by industry-sector groups. The objective is to analyze whether there is a contagion effect of the intensity of defaults from one sector to another as well as to examine one industry's vulnerability to credit defaults relative to another sector.

The two concepts of sector default vulnerability and infectivity are motivated by a series of past default events where large concentrations of defaults could reflect after-shocks of different crisis episodes. Some examples are as follows:

- The 1997 Asian crisis that involved vulnerable commodity prices and a deterioration in international trade.
- In 1998, the Long-Term Capital Management bailout implied a chain reaction in a wide number of financial firms.
- During 2000-2002, the dot-com bubble, which had being brewing since 1997, burst, dragging hundreds of technology and services companies into bankruptcy.

[4]Some exceptions can be made, which also constitutes one of the greatest criticisms of CRAs in recent years, e.g., the mortgage-backed securities and Enron major default events, for which CRAs had not assigned default credit ratings a few days before they collapsed.

- In 2001, the Enron collapse presented one of the major default events, affecting multiple energy-related firms' balance sheets and investor and creditor portfolios.

- As a result of the dot-com bubble, in 2002, Worldcom, the great telecommunications corporation, suffered one the largest accounting scandals and corporate bankruptcies of that time.

- Finally, the financial crisis that started in 2008 with the collapse of Lehman Brothers is the largest bankruptcy ever reported in U.S. history, involving the collapse of thousands of financial firms and banks and eventually becoming a global crisis.

We analyze the role of contagion in two directions, vulnerability and infectivity, and for this purpose, we propose a Multivariate Autoregressive Conditional Poisson model (MACP). Count processes seem to be suitable models for this type of default contagion since default events are measured by a integer number. We therefore model sectoral defaults as a multivariate count process following Heinen and Rengifo (2007). The use of this model allow us to estimate the degree of exposure of each sector to firms' defaults from other sectors, which we call vulnerability. Additionally, we are able to estimate the level of contagion that defaults from one sector can transmit to firms in the remaining industry groups.

The rest of the paper is organized as follows. Section 2 presents the historical data employed. In Section 3, we present our model to address the vulnerability and infectivity facets of credit contagion that we define. In Section 4, we present the main results of our analysis. Finally, Section 5 concludes the paper.

2 Data

In this paper, we use data on the debt default of firms domiciled in the U.S. during the time period starting on January 1, 1996, and ending on April 30, 2015. We identify default events using the Fixed Income Security Database (FISD) provided by Mergent, which includes rating history information from the three major credit rating agencies, Fitch, Moody's and Standard & Poors. They provide rating classes (AAA, AA, ..., D) depending on the creditworthiness of the issuer, and we retrieve the worst ratings for each rating agency that indicates an actual default.[5] We observe 5,078 bond defaults occurring over 1,126 days along the entire examined period of 4,868

[5]Fitch and Standard & Poors establish D as the worst rating, while Moody's follows a different classification and provides a rating of C to bonds in default.

working days.[6]

Most of the issuers have more than one bond outstanding, and they are sometimes rated by more than one CRA. In these cases, once any issuance of a firm is downgraded, the rest of the securities outstanding are also downgraded. Therefore, in order to consider multiple bond defaults on the same day as one firm default, we compute defaults at a firm level. Moreover, we also avoid duplicated defaults when more than one rating agency rates a firm. Additionally, in order to correct for those consecutive firms' defaults that could not be independently caused by parent-subsidiary relations, we disregard all defaults that occur within two months[7] surrounding any other default event from the same firm.[8] Finally, we obtain a sample of 1,284 daily firms' defaults that affected 997 different issuers distributed over different industry-sector groups.

Figure 1 shows the total number of firm credit defaults grouped per month. The largest number of defaults over one month occurs in April 2009, with 31 credit defaults registered. This period corresponds to the first months of the period of the recent global financial crisis that affected a large number of countries all over the world. Likewise, we can observe that the number of defaults seems to cluster around some of the crisis episodes mentioned above, for example, December 2001, when the Enron collapse occurred and the subsequent explosion of the dot-com bubble, and October 2008, which marks the beginning of the global financial crisis. In addition, we observe overdispersion of the distribution of the daily counts of defaults, since the empirical average of our sample is approximately 4.78 defaults per month, while the empirical variance is 35.62.

There is another particular feature of our data sample related to the calendar day on which defaults tend to occur. Figure 2 displays the distribution of default counts, and we can see that most defaults occur at the beginning and the middle of a month. This finding is consistent with the characteristics of our data sample since corporate bonds use to fix their corresponding coupon payments on the first and the fifteenth day of the month. When a rated firm fails on its payments, the CRA or CRAs that evaluate the creditworthiness of such a firm used to establish a grace period between one and five business days before they assign a default rating of either 'D' or 'SD'.[9] Although the tendency in Figure 2 is to observe defaults on days

[6] If a default occurs during a weekend or holidays, we consider the default to be the date of the next working day.

[7] Other authors, such as Lando and Nielsen (2010), employ a one-month window of days to avoid potential interrelated defaults.

[8] Since CRAs monitor credit rating assessments and re-rate the potential defaulting firms within a period of one month on average, this procedure of requiring a minimum period of two months between two consecutive defaults of the same firm ensures us that defaults are being treated as independent default events.

[9] Note that this rating assessment could be provisional, which is why a firm can suffer more than one rating default throughout its life. For instance, Standard and

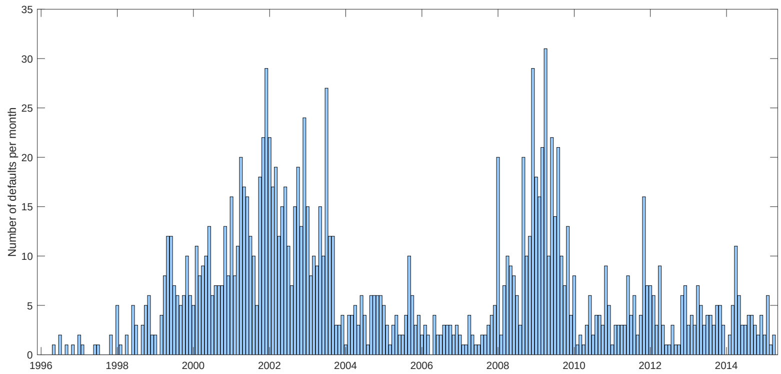

Figure 1: **Monthly number of defaults.** This figure shows the aggregate number of defaults per month over the period starting on January 1996 and ending on April 2015, extracted from rating history information reported by Mergent's FISD database.

2 and 16, which is in accordance with the periods in which rating agencies assign rating defaults for failed firms, we do not observe a large number of defaults on any particular calendar day; thus, our results should not be biased by this feature.

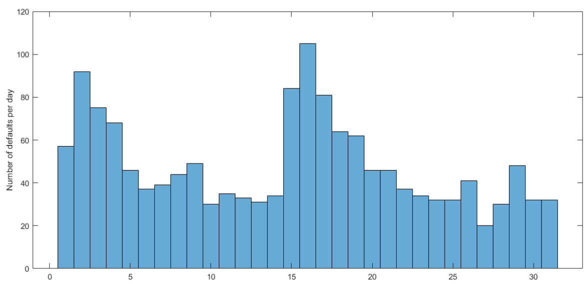

Figure 2: **Calendar day effects.** This figure shows the aggregate number of defaults on a calendar day over the period starting on January 1996 and ending on April 2015, extracted from rating history information reported by Mergent's FISD database.

To determine the existence and degree of the two transmission effects derived from the credit contagion phenomena, i.e., vulnerability and infectivity, we group the firms into the following industry sectors: industrial, financial, new technology, energy, utility, transportation and other sectors.

We consider these sectors the main and critical ones; they can act as the major sources of the two contagion effects that we aim to study. For example, the financial sector should be crucial in the financial crisis and

Poor's establishes different wide grace periods from one to five business days and a maximum of 30 calendar days for missed payments before assigning a rating of 'D' or 'SD' (see `https://www.spratings.com/documents/20184/774196/RatingsDirect_Commentary_1990483_Mar-06-2018_10_42.pdf`).

could act as a primary source of credit risk that could propagate to other sectors. This also true of the energy sector during the Enron crisis, in which credit problems could have started and then moved to the other industries. Figure 3 displays the distribution of the biweekly number of defaults by main sectors. We observe that the sectors with the majority of defaults are those of the industrial, financial and, to a lesser degree, new technology sectors. Moreover, these sectors are predominant within the two main crises that cover our data sample. We can see that industrial and new technology firms suffer most of the defaults during the years 2000 to 2003, whereas during the financial crisis period around 2008 and 2009, the vast number of defaults occur for financial companies. The late 2011 peak in the number of defaults in the transportation sector could be explained by the fact that this sector had the highest number of defaults in 2011, accounting for a total of eleven defaults during that year, with two defaults in August and nine in November, including American Airlines.

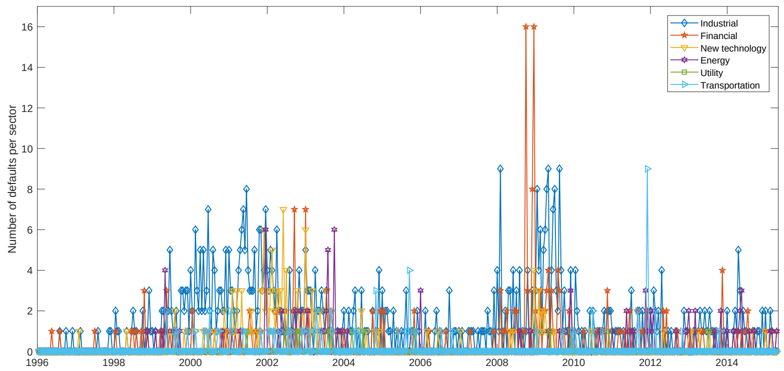

Figure 3: **Biweekly number of defaults by sector.** This figure shows the number of defaults by fortnight in the main considered sectors over the period starting on January 1996 and ending on April 2015, extracted from rating history information reported by Mergent's FISD database.

Table 1 shows the number of firm defaults distributed by industry group. We observe that the default rate in the sample equals 1.29, indicating that the number of defaults exceeds the number of firms.[10] The highest number of defaults occurs in firms within the industrial sector (663 defaults); meanwhile, the sector with the lowest number of defaults is the utility sector (13 defaults). The largest average number of defaults occurs in the "other" group, with 18 different firms that present an average number of 1.67 defaults per firm. On the other hand, the lowest default rate by sector is for transportation, with an average of approximately 1.16 defaults per firm. This distribution of defaults is in accordance with the higher number of in-

[10]Note that firms can suffer more than one credit rating default from their issuances over several years, which is why the number of defaults exceeds the number of firms.

dustrial firms relative to other types of firms and with the analyzed period that covers consecutive crises that have, to a greater or lesser extent, affected the industrial field.

	IND	FIN	NTEC	ENE	UTI	TRA	OTH	TOTAL
#defaults	663	231	169	106	13	72	30	1,284
#firms	528	156	138	86	9	62	18	997
Avg. #defaults per firm	1.26	1.48	1.22	1.25	1.44	1.16	1.67	1.29
Max. #defaults per firm	7	5	4	5	3	3	6	7
Min. #defaults per firm	1	1	1	1	1	1	1	1

Table 1: **Distribution of defaults.** This table shows the distribution of the firms' defaults across sectors over the period from January 1996 to April 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, *TRA*, and *OTH* refer to the industrial, financial, new technology, energy, utility, transportation and other sectors, respectively. Defaults are obtained with data from the FISD provided by Mergent.

3 The model and the covariates

Our aim is to study the evolution of the number of defaults in the various sectors and their interrelations. As such, our phenomenon is measured by an integer number, so count processes appear to be an appropriate model. We therefore model the sectoral defaults as a multivariate count process. Following Heinen and Rengifo (2007), we include an autoregressive component to account for the peculiar time evolution of the defaults (clusters and memory).

Consider a number K of sectors with $K = 1, ..., 7$. Let $N_{i,t}$ be the number of firm defaults in sector i during fortnight t.[11] We indicate $\{N_t\}$ the integer valued vector process or sectoral defaults, $N_t \in \mathbb{N}^K$.

We model the count process $\{N_t\}$ as a Multivariate Autoregressive Conditional Poisson (MACP) (Heinen and Rengifo, 2007). Let $\{\mathcal{F}_t\}$ be a filtration with respect to which the process $\{N_t\}$ is adapted. The conditional distribution of $N_{i,t}$ is assumed to be Poisson

$$N_{i,t} \mid \mathcal{F}_t \sim \text{Poi}(\lambda_{i,t}), \quad i = 1, \ldots, K,$$

with time-varying conditional intensities $\lambda_t \in \mathbb{R}^K$,

$$\lambda_t = \omega + \sum_{j=1}^{p} A_j N_{t-j} + \sum_{j=1}^{q} B_j \lambda_{t-j}, \tag{1}$$

where

$$\omega \in \mathbb{R}^K, \quad N_t \in \mathbb{N}^K, \quad A_j, B_j \in \mathbb{R}^{(K\times K)}, \forall j.$$

[11] According to the characteristics of our data sample shown in Figure 2, we consider biweekly data. We take the number of firm defaults within each fortnight of each month, i.e., the number of defaults from the 1st to the 14th day of the month and from the 15th to the last day of the month.

With full rank matrices A and B, great flexibility can be achieved at the cost of a large number of parameters, which increases quickly with K. For practical reasons, we limit the parameters' number setting $p = q = 1$, and more importantly, we restrict the matrices A and B as follows (see also Heinen and Rengifo, 2007)

$$A = \mathrm{diag}(a) + \gamma\delta' \, ; \qquad B = \mathrm{diag}(b) \tag{2}$$

with $a, b, \gamma, \delta \in \mathbb{R}^K$ column vectors. Moreover, in order to estimate the values of γ and δ, we impose the following condition $\gamma_K = 1 - \sum_{k=1}^{K-1} \gamma_k$.

Thanks to the formulation (2), we adopt the following interpretation of the parameters: parameter a_j measures the *own effect* of defaults in sector j. It measures the impact of a firm default in one sector on the intensity of other firms' defaults within the same sector. Parameter b_j assesses the *own memory effect* of sector intensity λ_j. It measures the persistence of the effect of a firm default within one specific sector. The vector γ collects the multipliers of the off-diagonal elements of the rows of matrix A. Hence, parameter γ_j measures the responsiveness of λ_j to firm defaults in other sectors, which we refer to as *sector vulnerability.* The entries of δ represent the multipliers of the off-diagonal elements of the columns of matrix A. Therefore, δ_j measures the influence of N_j on the other sectors' λs, which we refer to as *sector infectivity.*

To account for the effects of the exogenous variables on the count process, we introduce the dependence of the intensity λ_t from some variable X_t. Let $\{X\}$ be the process collecting the time series of H exogenous variables ($X_t \in \mathbb{R}^H$). Therefore, with $p = q = 1$, the time-varying conditional intensities are

$$\lambda_t = \omega + AN_{t-1} + B\lambda_{t-1} + C\left(X_{t-1}\right)', \tag{3}$$

where

$$\omega \in \mathbb{R}^K, \quad N_t \in \mathbb{N}^K, \quad A, B \in \mathbb{R}^{(K\times K)}, \quad C \in \mathbb{R}^{K\times H}$$

and the prime denotes the transposition to be consistent with the matrix product rules. Because λ_t cannot take negative values, we explicitly add a non-negative constraint on the values of λ_t.

As exogenous variables, we considered financial, real and macroeconomic indicators. The initial set of variables contains the following:

- The monthly Chicago Board Options Exchange Market Volatility Index (*VIX*) in order to control for the uncertainty in financial markets.
- The 10-year Treasury bond to 3-month Treasury bill monthly spread (*10Y-3m*), which represents the slope of the yield curve, to capture the appetite of investors for different maturities.
- The Baa to AAA Moody's rated monthly spread (*Baa-AAA*), which is strongly indicative of fundamental factors affecting default risk premia and can be viewed as an indicator of market distress.

- The 1-month return on the S&P500 index (*S&P*), which also captures financial market evolution.
- The real gross domestic product change from quarter one year ago (*GDP*) in order to control for the effects caused by greater fluctuations in general economic activity.
- The monthly smoothed recession probabilities (*RP*) in order to capture contracting economic cycles.
- The month-to-month change in the Industrial Production Index (*IP*) in order to control for domestic economic conditions.
- The monthly Leading Index (*LI*) in order to capture movements in external market conditions influencing U.S. asset prices.[12]

The returns on the S&P500 index have been previously used in other works, as in Duffie et al. (2007), Das et al. (2007), Lando and Nielsen (2010), Kramer and Löffler (2010) and Agosto et al. (2016). The changes in the Industrial Production Index have also been considered in Das et al. (2007), Lando and Nielsen (2010) and Agosto et al. (2016). The Leading Index has been used by Agosto et al. (2016). Similar to Lando and Nielsen (2010) and Kramer and Löffler (2010), we use a spread between two treasuries, the spread between the 10-year Treasury bond and the 3-month Treasury bill rates. Analogous to that in Agosto et al. (2016), we include the VIX index to control for the uncertainty in financial markets and the recession probabilities to control for business cycle expansions and contractions.

Table 2 shows the correlations and variance inflation factors (VIFs) among the exogenous variables. The Leading Index presents the largest correlation coefficients with other variables (see Panel A, Table 5). Moreover, the *LI* displays a VIF larger than 5 in the full set, which suggests that the level of directional connection among the independent variables is significant. These relations can be explained by the composition of this index.[13] As indicated by the Federal Reserve Economic Data (FRED), the Leading Index is computed on the basis of variables that are related to or coincide

[12] The time series data on the *GDP*, *RP*, *IP* and *LI* and data to compute the *Baa-AAA* spread are obtained from the Federal Reserve Economic Data (FRED) website, provided by the Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/`. The data to compute the *10Y-3m* spread have been obtained from the Federal Reserve (FED) web page, `https://www.federalreserve.gov/data.htm`. Time series of the S&P500 Index and the VIX Index have been obtained from the Investing and the Chicago Board Option Exchange (Cboe) websites: `https://www.investing.com/indices/us-spx-500`, and `http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data`, respectively.

[13] See Federal Reserve Bank of Philadelphia, Leading Index for the United States [USSLIND], retrieved from the FRED website, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/USSLIND`, July 17, 2018.

Panel A. Correlations								
	VIX	10Y-3m	Baa-AAA	S&P	GDP	RP	IP	LI
VIX	1.00	0.15	-0.58	-0.40	-0.39	0.52	-0.29	-0.55
10Y-3m	0.15	1.00	-0.34	-0.03	-0.39	0.17	-0.03	-0.24
Baa-AAA	-0.58	-0.34	1.00	0.14	0.75	-0.76	-0.06	0.79
S&P	-0.40	-0.03	0.14	1.00	0.14	-0.21	-0.10	0.18
GDP	-0.39	-0.39	0.75	0.14	1.00	-0.65	-0.16	0.81
RP	0.52	0.17	-0.76	-0.21	-0.65	1.00	0.02	-0.80
IP	-0.29	-0.03	-0.06	-0.10	-0.16	0.02	1.00	0.00
LI	-0.55	-0.24	0.79	0.18	0.81	-0.80	0.00	1.00
Panel B. Variance Inflation Factors								
VIF	VIX	10Y-3m	Baa-AAA	S&P	GDP	RP	IP	LI
full set	2.40	1.29	4.16	1.34	4.00	3.30	1.38	5.45
set 1	2.35	1.26	4.07	1.34	2.66	2.64	1.36	
set 2	1.83		2.96	1.21				2.76

Table 2: **Correlation matrix and variance inflation factors.** This table shows the correlation matrix between the exogenous variables in *Panel A* and the variance inflation factors (VIFs) for 3 sets of variables in *Panel B*. *VIX*, *10Y-3m*, *Baa-AAA*, *S&P*, *GDP*, *RP*, *IP* and *LI* refer to the Chicago Board Options Exchange Market Volatility Index, the 10-year Treasury bond to 3-month Treasury bill spread, the Baa to AAA Moody's rated spread, the return on the S&P500 index, the real change in gross domestic product change, the smoothed recession probabilities, the change in the Industrial Production Index, and the Leading Index, respectively. The time series data for the *GDP*, *RP*, *IP* and *LI* and the data to compute the *Baa-AAA* spread are obtained from the Federal Reserve Economic Data (FRED) website, provided by the Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/`. The data to compute the *10Y-3m* spread have been obtained from the Federal Reserve (FED) web page, `https://www.federalreserve.gov/data.htm`. Time series data for the S&P500 Index and the VIX Index have been obtained from the Investing and the Chicago Board Option Exchange (Cboe) websites `https://www.investing.com/indices/us-spx-500`, and `http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data`, respectively. The time series cover the period from January 1, 1996, to April 31, 2015.

with the 10-year Treasury bond to 3-month Treasury bill spread, the GDP quarterly change, the recession probability and the Industrial Production Index. For this reason, we chose to compare 2 different sets of variables: set 1 contains all the exogenous variables except the Leading Index, and set 2 includes the VIX, the Baa to AAA Moody's spread, the S&P return and the Leading Index. Note that these two sets of variables do not present extremely large correlation coefficients or VIF values. Additionally, to reduce some issues derived from the different scales of the exogenous variables, their values have previously been standardized.

The same analysis of exogenous correlation and collinearity has been performed on the two subperiods 1996-2005 and 2006-2015, generating very similar results; for the sake of interest and space, we do not report all details, but they are available upon request. Figure 4 displays the time series of the eight standardized exogenous variables.

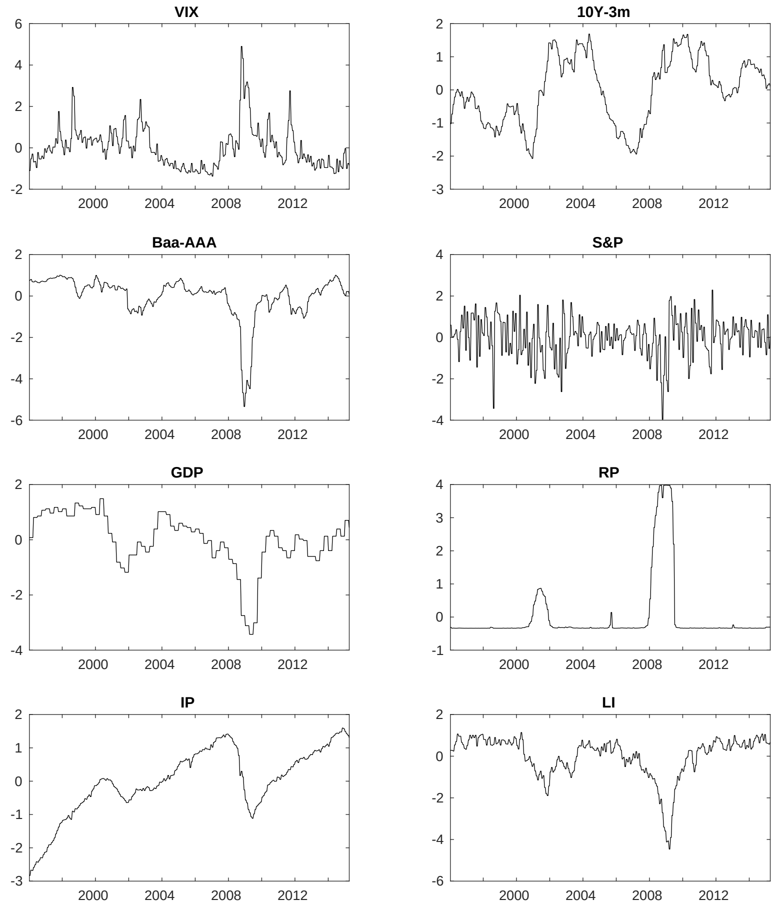

Figure 4: **Standardized exogenous time series.** This figure displays the time series of the exogenous variables considered in this study: the Chicago Board Options Exchange Market Volatility Index (*VIX*), the 10-year Treasury bond to 3-month Treasury bill spread (*10Y-3m*), the Baa to AAA Moody's rated spread (*Baa-AAA*), the return on the S&P500 index (*S&P*), the real change in gross domestic product change (*GDP*), the smoothed recession probabilities (*RP*), the change in the Industrial Production Index (*IP*), and the Leading Index (*LI*). The time series data for the *GDP*, *RP*, *IP* and *LI* and the data to compute the *Baa-AAA* spread are obtained from the Federal Reserve Economic Data (FRED) website, provided by the Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/`. The data to compute the *10Y-3m* spread have been obtained from the Federal Reserve (FED) web page, `https://www.federalreserve.gov/data.htm`. Time series data for the S&P500 Index and the VIX Index have been obtained from the Investing and the Chicago Board Option Exchange (Cboe) websites `https://www.investing.com/indices/us-spx-500`, and `http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data`, respectively. The time series cover the period from January 1, 1996, to April 31, 2015.

4 Results

We estimate the MACP model using the data presented in Section 2 by maximum likelihood. Some parameter constraints are imposed: $\omega \geq 0,\ a \geq 0,\ b \geq 0,\ \gamma \geq 0,\ \delta \geq 0$, and the stationarity and positiveness of λ_t.

The analysis is performed for the time period from January 1996 to April 2015, and as a robustness check, we carry out the same analysis on two subsamples to isolate two large default clusters. The first one covers the years from 1996 to 2005 and includes the "dot-com" bubble implosion episode, and the second one comprises the period from 2006 to 2015 and includes the global financial crisis years.[14]

For each time interval, three models are estimated: **Model 0**, the model without exogenous variables; **Model 1**, the model with the exogenous variables in set 1 (all exogenous variables, except the Leading Index); and **Model 2** the model with the exogenous variables in set 2 (the VIX, the Baa to AAA Moody's spread, the S&P return, the Leading Index).

4.1 Full sample

Tables 3, 4 and 5 show the estimation results for the full sample (1996-2015). We report the output of all three models, although the information criteria and the likelihood ratio test identify Model 0 as the best one. A significant own effect (parameter a) is present in the industrial, financial, new technology and energy sectors (this holds for all three models). These are also the sectors with the largest number of defaults, as shown in Table 1. Hence, in these sectors, the probability of a firm suffering a default increases when another company in the same sector suffers a default; i.e., there is a contagion effect within the industrial, financial and new technology sectors.

If we look at the own memory effect (value of parameter b), we find that the coefficient is highly statistically significant in the industrial, financial, new technology and energy sectors; Model 1 indicates a significant effect on all sectors. This result suggests that the effect derived from a firm default tends to remain persistent over time within the firm's sector, which could explain the clustering of defaults during some periods.

Regarding the vulnerability effect (parameter γ), the three models produce different results. All models find statistically significant loadings for the energy sector, although the result is weak for Model 0. The utility sector has a significant γ in Models 0 and 1; for the industrial sector, the parameter γ is significant only in Model 1. These results indicate that these industries are the sectors most vulnerable to defaults, meaning that firms' defaults

[14]Notably, the Augmented Dickey-Fuller test performed on the number of sector defaults N_t rejects the unit root hypothesis for all sectors, for the full sample and for the two subperiods, at the 1% level.

occurring in other sectors more strongly affect the occurrence of defaults in the industrial, energy and utility sectors.

Moreover, the results for the infectivity effect suggest that the only sector with a strong, significant contagion effect across all models is the new technology sector. This finding indicates that firm defaults starting in companies from the new technology sector more strongly affect defaults occurring in other firms from other sectors. Moreover, the energy sector has a significant coefficient, although it is weak for Model 0. The industrial sector has a significant coefficient in Models 1 and 2, and the financial sector has a significant coefficient in Model 0 (weak) and Model 2.

Finally, the exogenous variables do not seem to have a substantial contribution. In fact, the information criteria and the likelihood ratio test indicate that the model without exogenous variables is the best one. Moreover, the pseudo R^2 value weakly increases from Model 0 to the models with exogenous variables.[15] Moreover, the finding of significant exogenous effects for the utility sector in Model 1 and for the energy sector in Model 2 may indicate the undesirable instability of the estimation procedure.

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0350*	0.0178*	0.0035	0.0063	0.0022	0.0311
	(0.0173)	(0.0081)	(0.0039)	(0.0142)	(0.0061)	(0.0207)
a	0.1598***	0.1031***	0.1501***	0.0802*	0.0071	0.0061
	(0.0282)	(0.0221)	(0.0391)	(0.0366)	(0.1225)	(0.0478)
b	0.7881***	0.8376***	0.7782***	0.7514***	0.3959	0.4054*
	(0.0167)	(0.0310)	(0.0547)	(0.1125)	(0.2921)	(0.1925)
γ	0.1857	0.0686•	0.1145*	0.1890•	0.0948**	0.3474
	(0.1669)	(0.0360)	(0.0575)	(0.1060)	(0.0338)	(1.0000)
δ	0.0324	0.0537	0.1042**	0.1841***	0.0099	0.0887
	(0.0231)	(0.0668)	(0.0330)	(0.0495)	(0.2343)	(0.0860)
logl	-1966.9229					
AIC	3991.8					
BIC	4111.8					
pseudo R^2	0.2829					

Table 3: **Model 0 parameter estimates for the whole sample.** This table shows the main results from Equations (1) and (2) for the sample that comprises the period from January 1996 to April 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

We can see in Figure 5 that, principally for the sectors with the largest number of defaults, the estimated intensity closely follows the evolution of the default time series. In addition, if we look at the first half of the sample, the second sector in terms of intensity is the new technology sector. By

[15]The pseudo R^2 value is evaluated with respect to the Poisson model with $\lambda_{i,t} = E\left[N_{i,s}, s < t\right], i = 1, \ldots, K$; that is, for each sector, the intensity at time t equals the average number of defaults up to time t.

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0350	0.0178	0.0035	0.0063***	0.0022***	0.0311**
	(0.0321)	(0.0109)	(0.0072)	(0.0017)	(0.0000)	(0.0107)
a	0.1598**	0.1031*	0.1501***	0.0802*	0.0071	0.0061
	(0.0521)	(0.0517)	(0.0364)	(0.0398)	(0.1689)	(0.0531)
b	0.7881***	0.8375***	0.7782***	0.7514***	0.3959***	0.4054***
	(0.0660)	(0.0636)	(0.1143)	(0.0445)	(0.0178)	(0.0501)
γ	0.1857**	0.0686	0.1145	0.1890***	0.0948***	0.3474
	(0.0635)	(0.0597)	(0.0955)	(0.0530)	(0.0266)	(1.0000)
δ	0.0324***	0.0537	0.1042***	0.1841***	0.0099	0.0887
	(0.0081)	(0.0329)	(0.0113)	(0.0403)	(0.2716)	(0.0811)
VIX	0.0042	0.0025	0.0012	0.0006	-0.0003***	0.0002
	(0.0181)	(0.0105)	(0.0064)	(0.0041)	(0.0000)	(0.0188)
10Y-3m	0.0002	0.0009	-0.0003	0.0023	0.0014***	-0.0000
	(0.0145)	(0.0053)	(0.0012)	(0.0078)	(0.0000)	(0.0119)
Baa-AAA	0.0023	0.0015	0.0007	-0.0001	0.0001***	0.0010
	(0.0267)	(0.0149)	(0.0084)	(0.0109)	(0.0000)	(0.0286)
S&P	0.0020	-0.0009	-0.0005	0.0011	0.0001***	0.0000
	(0.0255)	(0.0158)	(0.0055)	(0.0131)	(0.0000)	(0.0183)
GDP	0.0039	-0.0010	0.0010	-0.0004	-0.0001***	0.0007
	(0.0260)	(0.0116)	(0.0119)	(0.0119)	(0.0000)	(0.0208)
RP	0.0029	0.0047	0.0019	0.0002	-0.0002***	0.0001
	(0.0271)	(0.0129)	(0.0073)	(0.0099)	(0.0000)	(0.0348)
IP	0.0012	0.0016	-0.0002	0.0019	0.0004***	0.0007
	(0.0141)	(0.0071)	(0.0042)	(0.0047)	(0.0000)	(0.0333)
logl	-1957.7515					
AIC	4057.5					
BIC	4351.3					
pseudo R^2	0.2864					

Table 4: **Model 1 parameter estimates for the whole sample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from January 1996 to April 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

contrast, in the second half of the sample, the financial sector is the second leading sector in terms of intensity. This result suggests that the model is able to detect the overall difference between the two main default clusters of recent decades, i.e., the dot-com bubble implosion driven by new technology sector and the global financial crisis driven by the financial sector.

The implied lambdas for Models 1 and 2 are reported in Figures A.1 and A.2 in the Technical Appendix. Note that the inclusion of the exogenous does not add a visible contribution. Moreover, Table A.1, panel A and Figure A.7 show the result for Model 0 with the restrictions delta=gamma=0, i.e. no infectivity and contagion effects. We remark that the likelihood ratio test rejects the restrictions.

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0329	0.0187•	0.0036	0.0000***	0.0000	0.0293
	(0.0223)	(0.0098)	(0.0056)	(0.0000)	(0.0065)	(0.0528)
a	0.1591***	0.0997***	0.1434***	0.0677**	0.0000	0.0000
	(0.0294)	(0.0295)	(0.0399)	(0.0223)	(0.1522)	(0.0441)
b	0.7894***	0.8343***	0.7875***	0.7988***	0.4129*	0.4386
	(0.0402)	(0.0387)	(0.0529)	(0.0000)	(0.1750)	(0.2917)
γ	0.1845	0.0731	0.1132	0.1788***	0.1012	0.3493
	(0.2379)	(0.0639)	(0.0779)	(0.0000)	(0.0698)	(1.0000)
δ	0.0349***	0.0525***	0.0826***	0.1806*	0.0001	0.1002***
	(0.0000)	(0.0000)	(0.0000)	(0.0785)	(0.2382)	(0.0028)
VIX	0.0043	0.0055	0.0033	0.0022***	-0.0003	-0.0003
	(0.0131)	(0.0063)	(0.0036)	(0.0000)	(0.0148)	(0.0193)
Baa-AAA	-0.0015	-0.0043	0.0005	-0.0033***	0.0003	0.0008
	(0.0249)	(0.0124)	(0.0075)	(0.0000)	(0.0165)	(0.0260)
S&P	-0.0017	-0.0050	-0.0016	0.0042***	-0.0006	-0.0012
	(0.0233)	(0.0134)	(0.0109)	(0.0000)	(0.0106)	(0.0263)
LI	-0.0020	-0.0052	-0.0009	0.0043***	0.0004	0.0029
	(0.0255)	(0.0102)	(0.0069)	(0.0000)	(0.0215)	(0.0211)
logl	-1955.2005					
AIC	4016.4					
BIC	4235.7					
pseudo R^2	0.2881					

Table 5: **Model 2 parameter estimates for the whole sample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from January 1996 to April 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

4.2 Period from 1996 to 2005

The results from the first subsample (1996-2005) are displayed in Tables 6, 7 and 8. According to our findings, the industrial and energy sectors present a significant own effect across all models; however, the own effect is significant for the new technology sector only in Model 0. Again, these are the sectors with the largest number of defaults. These results suggest that the model is able to detect an intrasectoral contagion effect. The coefficient of the own memory effect is statistically significant for all sectors except the utility sector, only in Model 0. In this case, the intensity of defaults seems to persist over time in almost all sectors. However, concerning the vulnerability effect, the models do not agree: Model 0 has a significant γ parameter for the new technology sector but a barely significant one for the financial sector. The other two models provide different results. During this period, which includes the dot-com bubble implosion, the new technology sector seems to have suffered from a vulnerability effect coming from defaults in other sectors. In addition, we find that coefficients of the infectivity effect are statistically significant for the industrial sector across all models, whereas Model 0 indicates a significant effect for the new technology and transportation sectors. This result indicates that firm defaults in these sectors are contagious to other firms belonging to other sectors. Finally, all of the considered exogenous variables are statistically significant only for the utility sector, but with very small coefficient values. However, Model 0 with no exogenous turns out to be the best one concerning the information criteria and the likelihood ratio test.

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0002	0.0096**	0.0000	0.0000	0.0000	0.0000
	(0.0021)	(0.0035)	(0.0039)	(0.0094)	(0.0998)	(0.0017)
a	0.1214***	0.0000	0.1121*	0.1062**	0.0000	0.0000
	(0.0338)	(0.0200)	(0.0535)	(0.0402)	(0.8222)	(0.0185)
b	0.8770***	0.9061***	0.7889***	0.7126***	0.0001	0.9655***
	(0.0061)	(0.0428)	(0.0672)	(0.0791)	(0.0132)	(0.0039)
γ	0.0000	0.1496•	0.3226***	0.2578	0.2251	0.0449
	(0.1128)	(0.0775)	(0.0725)	(0.2290)	(0.1763)	(1.0000)
δ	0.0475**	0.0533	0.1045**	0.0109	0.0000	0.0373***
	(0.0171)	(0.0649)	(0.0355)	(0.0751)	(0.5786)	(0.0081)
logl	-1064.2020					
AIC	2186.4					
BIC	2290.1					
pseudo R^2	0.2493					

Table 6: **Model 0 parameter estimates for the first subsample.** This table shows the main results from Equations (1) and (2) for the sample that comprises the period from 1996 to 2005. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

Figure 6 plots the implied λs for the first subsample (1996-2005). We emphasize that when we restrict the sample to the first half, the relevance of default intensity for new technology firms is confirmed, since the largest peaks in the values of the implied λs occur around the beginning and middle of 2002. Also in this subperiod, the estimated intensity closely follows the evolution of the default time series.

The implied lambdas for Models 1 and 2 are reported in Figures A.3 and A.4 in the Technical Appendix. Note that the inclusion of the exogenous does not add a visible contribution. Moreover, Table A.1, panel B and Figure A.9 show the result for Model 0 with the restrictions delta=gamma=0, i.e. no infectivity and contagion effects. We remark that the likelihood ratio test rejects the restrictions.

4.3 Period from 2006 to 2015

In Tables 9, 10 and 11, we show the main results for the second subsample from January 2006 to April 2015. Notably, a significant own effect is present in the industrial, financial, new technology and energy sectors. The results

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0002	0.0096	0.0000	0.0000	0.0000***	0.0000
	(0.0004)	(0.0073)	(0.0120)	(0.0212)	(0.0000)	(0.0034)
a	0.1214***	0.0000	0.1121	0.1062•	0.0000	0.0000
	(0.0307)	(0.0069)	(0.1661)	(0.0606)	(1.8604)	(0.0089)
b	0.8769***	0.9061***	0.7889***	0.7126***	0.0001***	0.9655***
	(0.0242)	(0.0364)	(0.1130)	(0.0088)	(0.0000)	(0.0056)
γ	0.0000	0.1496***	0.3226•	0.2578**	0.2251***	0.0449
	(0.0413)	(0.0407)	(0.1760)	(0.0970)	(0.0046)	(1.0000)
δ	0.0475***	0.0533	0.1045	0.0109	0.0000	0.0373
	(0.0010)	(0.0481)	(0.0852)	(0.0244)	(0.1874)	(0.0716)
VIX	0.0004	0.0003	0.0002	0.0001	-0.0001***	0.0001
	(0.0106)	(0.0102)	(0.0111)	(0.0170)	(0.0000)	(0.0049)
10Y-3m	-0.0001	-0.0000	0.0002	0.0000	-0.0000***	-0.0002
	(0.0117)	(0.0038)	(0.0065)	(0.0223)	(0.0000)	(0.0025)
Baa-AAA	0.0003	0.0004	0.0004	0.0003	0.0001***	0.0002
	(0.0302)	(0.0175)	(0.0358)	(0.0405)	(0.0000)	(0.0082)
S&P	0.0003	0.0001	0.0001	0.0001	-0.0000***	0.0000
	(0.0153)	(0.0151)	(0.0491)	(0.0243)	(0.0000)	(0.0097)
GDP	0.0003	0.0001	0.0005	0.0002	0.0001***	0.0003
	(0.0335)	(0.0102)	(0.0333)	(0.0319)	(0.0000)	(0.0095)
RP	0.0018	0.0001	0.0002	0.0002	0.0001***	0.0002
	(0.0545)	(0.0275)	(0.0761)	(0.0649)	(0.0000)	(0.0053)
IP	-0.0000	-0.0000	-0.0000	0.0001	0.0000***	0.0006
	(0.0059)	(0.0032)	(0.0104)	(0.0355)	(0.0000)	(0.0015)
logl	-1062.2931					
AIC	2266.6					
BIC	2520.5					
pseudo R^2	0.2504					

Table 7: **Model 1 parameter estimates for the first subsample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from 1996 to 2005. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

are quite stable across models. In this case, it is also confirmed that these sectors have the largest number of defaults. Therefore, the model performs well in detecting intrasectoral contagion effects, similar to its performance in the first subsample. Additionally, the own memory is significant for all sectors except the transportation sector. We remark that in this period, almost all sectors are significantly vulnerable, and all sectors are significantly contagious. This result is quite consistent across models. Finally, information criteria and likelihood ratio tests also indicate that the best model is the one without exogenous variables. We note that all exogenous effects are significant for the utility sectors in Model 1, but none of them is significant in Model 2.

In Figure 7, we display the estimation results for this subsample (2006-2015). We remark that when we restrict the sample to the second half, the relevance of the default intensity for the financial sector is confirmed, as

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0002	0.0096	0.0000	0.0000	0.0000***	0.0000
	(0.0006)	(0.0354)	(0.0227)	(0.0160)	(0.0000)	(0.0037)
a	0.1214***	0.0000	0.1121	0.1062**	0.0000	0.0000
	(0.0268)	(0.0296)	(0.0865)	(0.0331)	(1.1429)	(0.0273)
b	0.8770***	0.9061***	0.7889***	0.7126***	0.0001***	0.9655***
	(0.0270)	(0.0369)	(0.0870)	(0.0436)	(0.0000)	(0.0186)
γ	0.0000	0.1496	0.3226	0.2578*	0.2251***	0.0449
	(0.0418)	(0.1859)	(0.2703)	(0.1031)	(0.0046)	(1.0000)
δ	0.0475***	0.0533	0.1045	0.0109	0.0000	0.0373
	(0.0010)	(0.0775)	(0.1472)	(0.0650)	(0.4276)	(0.0416)
VIX	0.0004	0.0004	0.0002	0.0001	-0.0000***	0.0001
	(0.0069)	(0.0128)	(0.0089)	(0.0034)	(0.0000)	(0.0036)
Baa-AAA	0.0003	0.0004	0.0005	0.0002	0.0000***	0.0002
	(0.0250)	(0.0116)	(0.0182)	(0.0175)	(0.0000)	(0.0030)
S&P	0.0002	0.0001	0.0001	0.0001	-0.0000***	0.0000
	(0.0127)	(0.0138)	(0.0144)	(0.0222)	(0.0000)	(0.0178)
LI	0.0011	0.0001	0.0005	0.0001	0.0000***	0.0002
	(0.0247)	(0.0074)	(0.0283)	(0.0269)	(0.0000)	(0.0103)
logl	-1060.0261					
AIC	2226.1					
BIC	2415.6					
pseudo R^2	0.2491					

Table 8: **Model 2 parameter estimates for the first subsample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from 1996 to 2005. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

we can observe that the implied λs increase dramatically around the end of 2008 and the beginning of 2009.

The implied lambdas for Models 1 and 2 are reported in Figures A.5 and A.6 in the Technical Appendix. Note that the inclusion of the exogenous does not add a visible contribution. Moreover, Table A.1, panel C and Figure A.9 show the result for Model 0 with the restrictions delta=gamma=0, i.e. no infectivity and contagion effects. We remark that the likelihood ratio test rejects the restrictions.

5 Conclusions

This paper analyzes credit rating default dependencies in a multisectoral framework. Using Mergent's FISD database, we study the default series in the U.S. over the last two decades, disaggregating defaults by industry-sector groups. During this period, two main waves of default occurred: the implosion of the "dot-com" bubble and the global financial crisis. We estimate a Multivariate Autoregressive Conditional Poisson (MACP) model on the number of defaults in a fortnight that have occurred in different

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0000	0.0059***	0.0004***	0.0088***	0.0000***	0.0112***
	(0.0000)	(0.0010)	(0.0000)	(0.0003)	(0.0000)	(0.0029)
a	0.3656***	0.0914**	0.0785***	0.1131***	0.0009	0.0010
	(0.0235)	(0.0282)	(0.0075)	(0.0053)	(0.2458)	(0.0146)
b	0.7062***	0.7722***	0.4669***	0.3260***	0.4378•	0.8984***
	(0.0262)	(0.0283)	(0.0070)	(0.0072)	(0.2451)	(0.0107)
γ	0.0013***	0.2780***	0.2437***	0.4368***	0.0403***	0.0000
	(0.0000)	(0.0074)	(0.0022)	(0.0049)	(0.0048)	(1.0000)
δ	0.2133***	0.0001***	0.0082***	0.0007***	0.1378***	0.0000***
	(0.0099)	(0.0000)	(0.0000)	(0.0000)	(0.0049)	(0.0000)
logl	-920.2687					
AIC	1898.5					
BIC	1994.0					
pseudo R^2	0.1658					

Table 9: **Model 0 parameter estimates for the second subsample.** This table shows the main results from Equations (1) and (2) for the sample that comprises the period from 2006 to 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

sectors of the economy.

Our results show that the model is able to describe the default time series and allows a consistent interpretation of the two main waves of defaults in recent decades. In general, the persistence of lambdas is significant, and this helps to explain default clustering.

We also discuss the contagion effect between sectors in two ways: the degree of transmission of the probability of default from one sector to another, i.e., the "infectivity" of the sector, and the degree of contagion of one sector from another, i.e., the "vulnerability" of the sector. We find that the own effects, i.e., intrasectoral contagion, are significant in the sectors with the largest number of defaults. For these sectors, the own effect seems to be more important than intersectoral contagion in explaining the time series of the defaults.

To better detect intersectoral contagion, we split the sample into two subsamples. The separate analysis of the two subperiods sheds light on the sectoral dependencies, since we observe some differences between the sectors' relations during the first and second parts of our sample. In fact, for the full sample, these effects can be difficult to disentangle, probably because of the divergent nature of the two main default clusters. In the first subperiod, the selected model detects the infectivity and vulnerability of the new technology sector. This finding was expected, although the result is not stable across the model specifications. Instead, in the second subsample, a general result to highlight is that in this period, all sectors seem interconnected with regard to infectivity and vulnerability. This result can be interpreted as a feature of the global financial crisis, whose effects spread throughout the whole

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0000	0.0059	0.0004***	0.0088***	0.0000***	0.0112***
	(0.0000)	(0.0049)	(0.0000)	(0.0012)	(0.0000)	(0.0018)
a	0.3656***	0.0914***	0.0785	0.1131**	0.0009	0.0010
	(0.0490)	(0.0099)	(0.0632)	(0.0356)	(0.0072)	(0.0117)
b	0.7062***	0.7722***	0.4669***	0.3260***	0.4378***	0.8984***
	(0.0500)	(0.1484)	(0.0630)	(0.0661)	(0.0002)	(0.0123)
γ	0.0013	0.2780*	0.2437*	0.4368***	0.0403***	0.0000
	(0.0052)	(0.1063)	(0.1114)	(0.0465)	(0.0000)	(1.0000)
δ	0.2133***	0.0001	0.0082***	0.0007***	0.1378	0.0000***
	(0.0139)	(0.0001)	(0.0000)	(0.0001)	(0.1471)	(0.0000)
VIX	-0.0061	0.0010	0.0002	-0.0001	0.0002***	0.0023
	(0.0459)	(0.0150)	(0.0683)	(0.0157)	(0.0000)	(0.0081)
10Y-3m	-0.0060	0.0007	-0.0007	0.0014	0.0002***	0.0014
	(0.0245)	(0.0065)	(0.0277)	(0.0195)	(0.0000)	(0.0092)
Baa-AAA	0.0000	0.0028	0.0017	0.0007	0.0002***	0.0004
	(0.0427)	(0.0272)	(0.0192)	(0.0145)	(0.0000)	(0.0114)
S&P	0.0021	0.0006	-0.0012	0.0006	0.0002***	0.0001
	(0.0518)	(0.0305)	(0.0582)	(0.0154)	(0.0000)	(0.0248)
GDP	0.0028	0.0017	-0.0008	0.0006	-0.0000***	0.0011
	(0.0505)	(0.0449)	(0.0249)	(0.0268)	(0.0000)	(0.0114)
RP	-0.0004	0.0039	-0.0009	0.0004	-0.0001***	-0.0005
	(0.0317)	(0.0113)	(0.0310)	(0.0224)	(0.0000)	(0.0169)
IP	0.0075	0.0007	0.0023	0.0012	0.0002***	0.0001
	(0.0309)	(0.0143)	(0.0299)	(0.0092)	(0.0000)	(0.0110)
logl	-917.6704					
AIC	1977.3					
BIC	2211.2					
pseudo R^2	0.1684					

Table 10: **Model 1 parameter estimates for the seconds subsample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from 2006 to 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

economy, affecting every sector.

Finally, we add to the analysis some exogenous variables and evaluate their contribution to the goodness of fit. However, the inclusion of these variables does not appear to indicate a relevant contribution to the goodness of fit of the model.

	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0000	0.0059***	0.0004***	0.0088***	0.0000***	0.0112***
	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0027)
a	0.3656***	0.0914*	0.0785***	0.1131***	0.0009	0.0010
	(0.0172)	(0.0366)	(0.0060)	(0.0059)	(0.1642)	(0.0183)
b	0.7062***	0.7722***	0.4669***	0.3260***	0.4378**	0.8984***
	(0.0193)	(0.0368)	(0.0060)	(0.0085)	(0.1641)	(0.0102)
γ	0.0013***	0.2780***	0.2437***	0.4368***	0.0403***	0.0000
	(0.0000)	(0.0029)	(0.0137)	(0.0058)	(0.0024)	(1.0000)
δ	0.2133***	0.0001***	0.0082***	0.0007***	0.1378***	0.0000***
	(0.0041)	(0.0000)	(0.0000)	(0.0000)	(0.0061)	(0.0000)
VIX	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0182)	(0.0383)	(0.0143)	(0.0355)	(0.0055)
Baa-AAA	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0217)	(0.0067)	(0.0123)	(0.0202)	(0.0081)
S&P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0338)	(0.0335)	(0.0115)	(0.0463)	(0.0092)
LI	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0193)	(0.0333)	(0.0184)	(0.0408)	(0.0060)
logl	-920.2516					
AIC	1946.5					
BIC	2121.0					
pseudo R^2	0.1658					

Table 11: **Model 2 parameter estimates for the second subsample.** This table shows the main results from Equations (2) and (3) for the sample that comprises the period from 2006 to 2015. *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, and *TRA* refer to the industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The exogenous variables in the table are the same as appearing in Table 2. The number of defaults are obtained with data from the FISD database provided by Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, FED, Investing and Cboe websites. Asymptotic standard errors are reported in parenthesis. The symbols ***, **, * and • indicate statistical significance at the 0.1%, 1%, 5% and 10% levels, respectively.

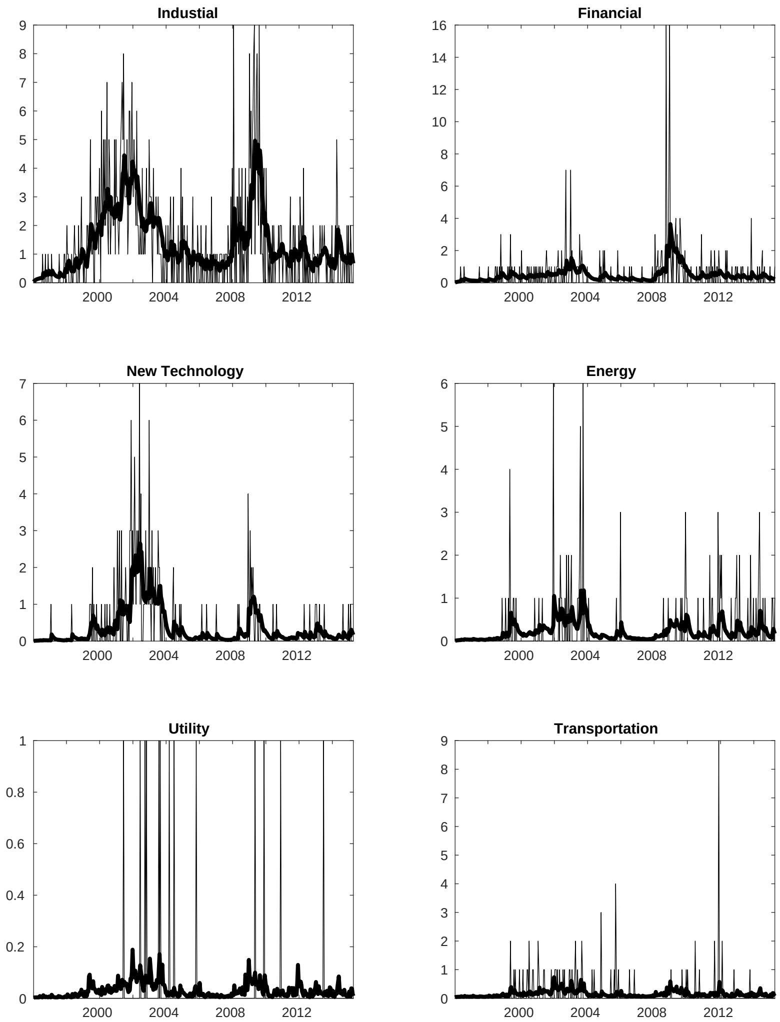

Figure 5: **Model 0 estimated intensities for the whole sample.** This figure displays the implied λs that are computed on the basis of the results displayed in Table 3 for the whole sample. The intensities (bold lines) are compared to the actual number of defaults (thin lines).

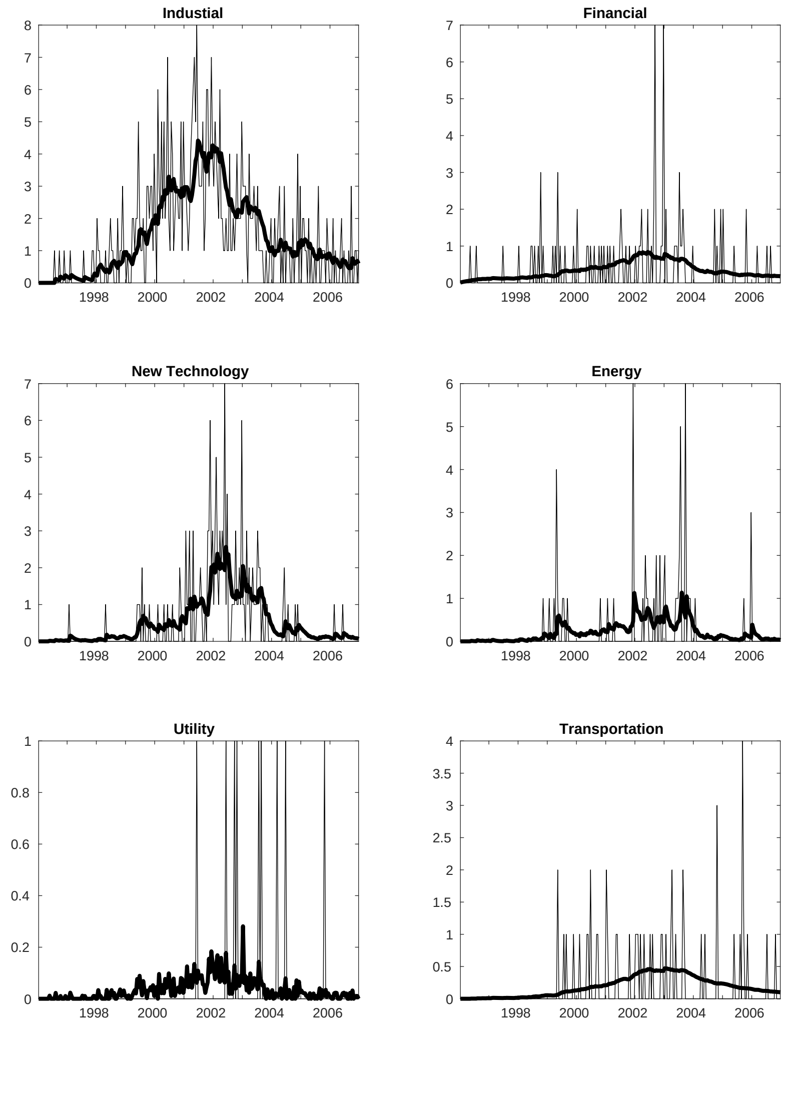

Figure 6: **Model 0 estimated intensities in the period 1996-2005.** This figure displays the implied λs that are computed on the basis of the results displayed in Table 6. The intensities (bold lines) are compared to the actual number of defaults (thin lines).

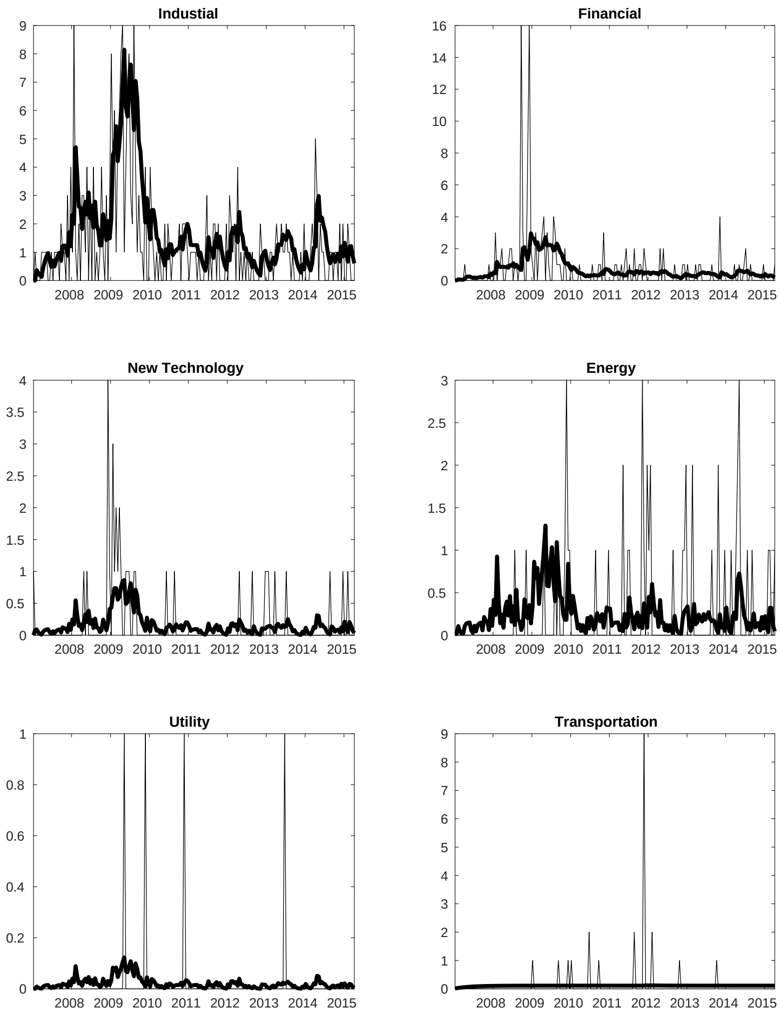

Figure 7: **Model 0 estimated intensities in the period 2006-2015.** This figure displays the implied λs that are computed on the basis of the results displayed in Table 9. The intensities (bold lines) are compared to the actual number of defaults (thin lines).

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A. Technical Appendix

This appendix collects some additional estimation results, concerning model specifications with worse performances than the one presented in the main part of the paper.

A.1 Models 1 and 2 results

Figures from A.1 to A.6 show the implied λs for Models 1 and 2. Remark that the behaviors are very close to the ones obtained by Model 0, therefore, the inclusion of the exogenous does not seem to add a visible contribution.

A.2 No infectivity and contagion

Table A.1 and Figures A.7, A.8 and A.9 report the results of the estimation of a rstricted model with $\gamma = \delta = 0$. Information criteria and likelihood ratio tests indicate that the restrictions are rejected. This means that the infectivity and contagion effects are significant and help in explaining the phenomenon at study.

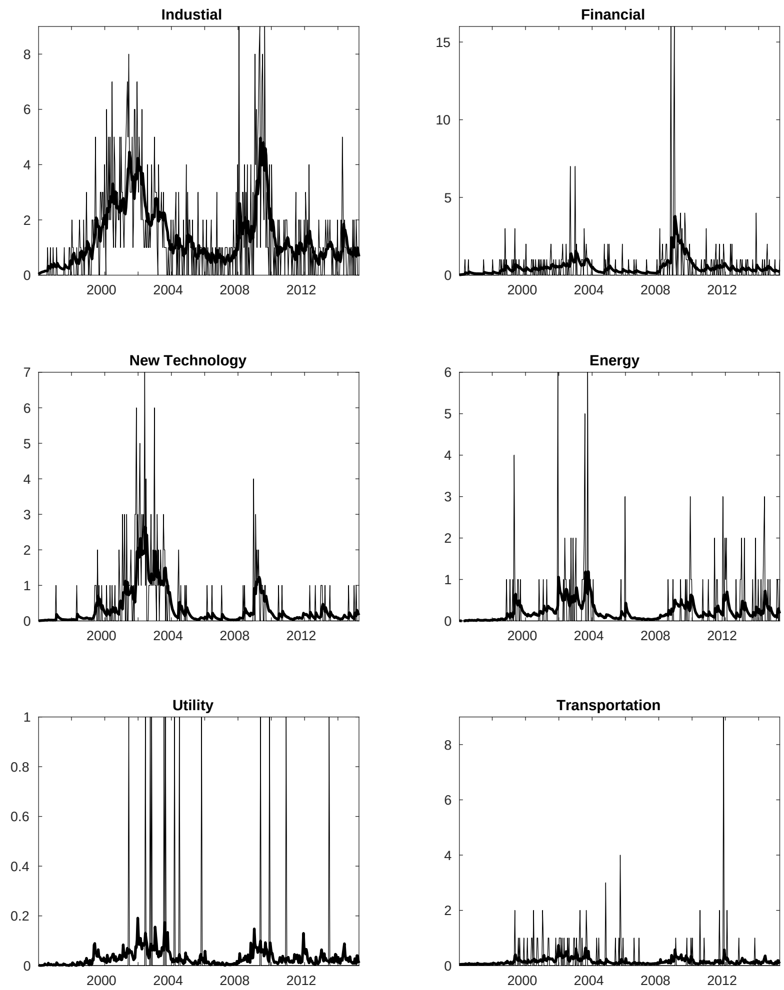

Figure A.1: Implied λs for Model 1, entire period (1996-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

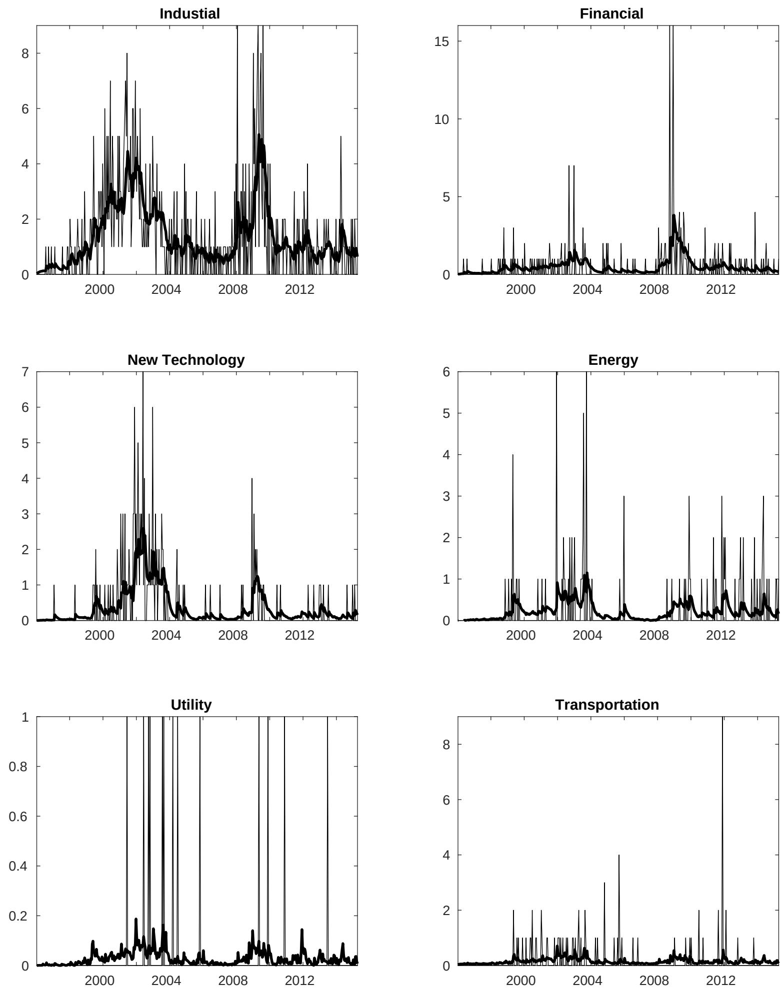

Figure A.2: Implied λs for Model 2, entire period (1996-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

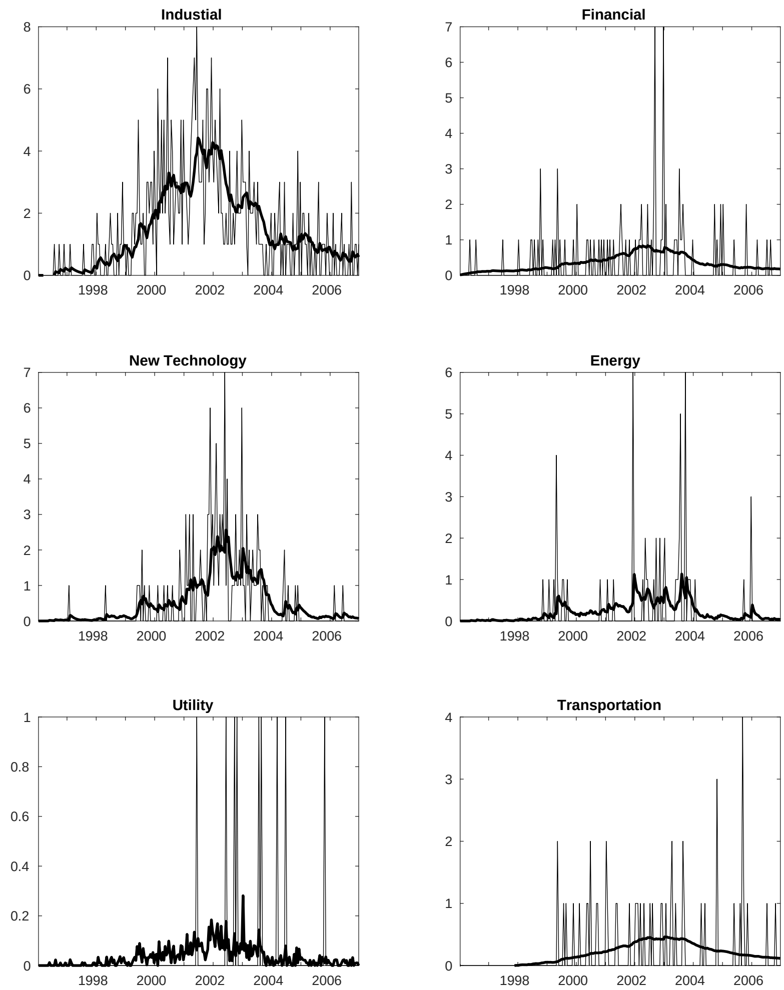

Figure A.3: Implied λs for Model 1, first period (1996-2005). Bold lines refer to the intensities and thin lines to the actual number of defaults.

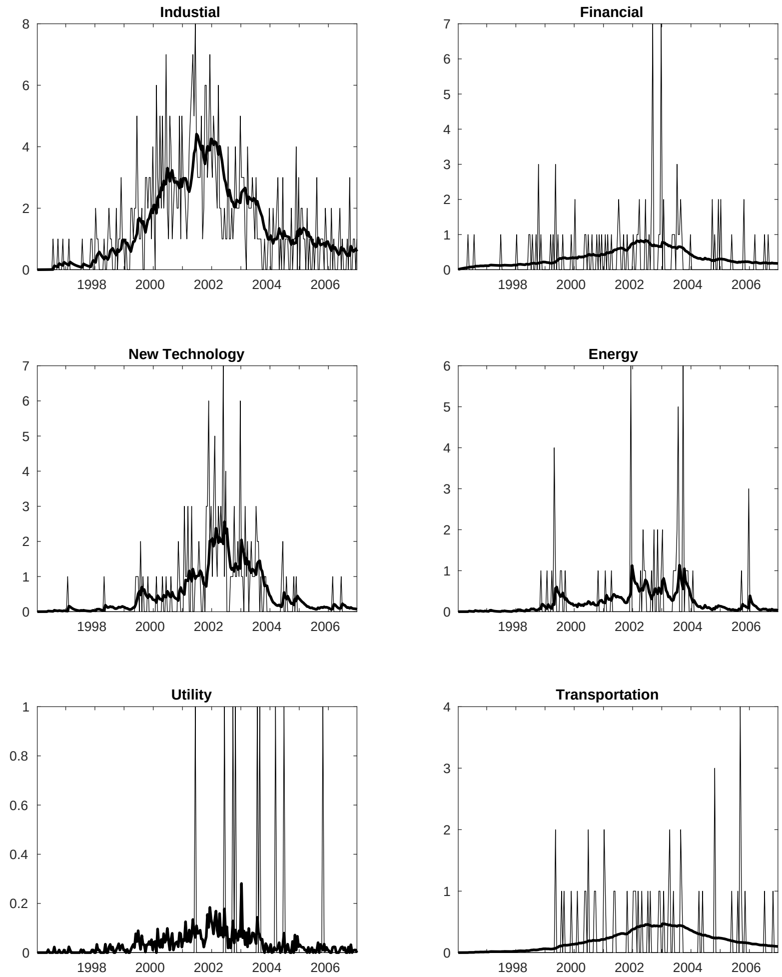

Figure A.4: Implied λs for Model 2, first period (1996-2005). Bold lines refer to the intensities and thin lines to the actual number of defaults.

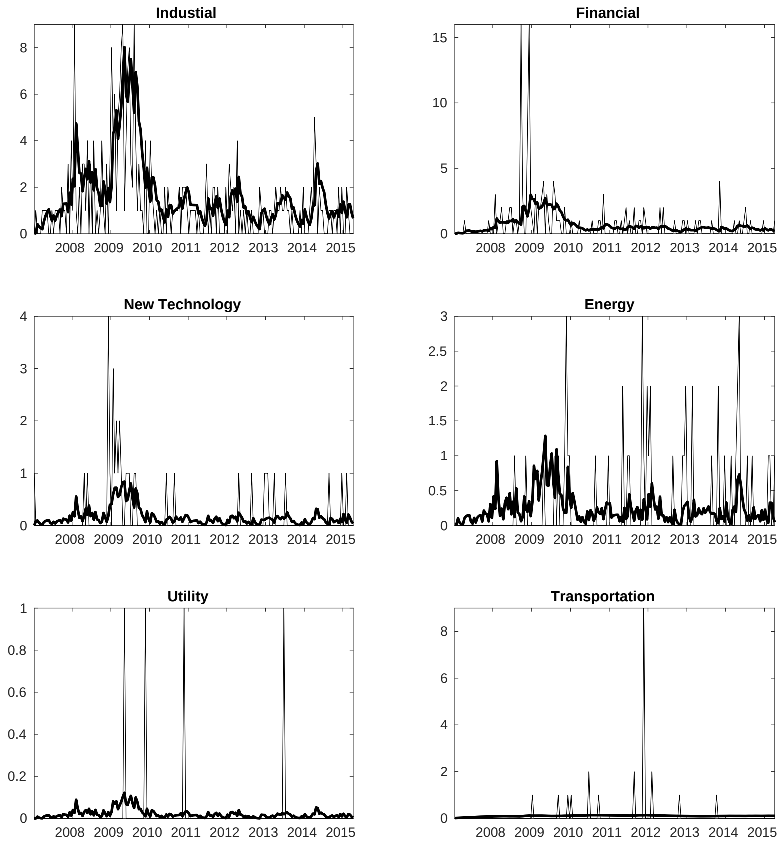

Figure A.5: Implied λs for Model 1, second period (2006-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

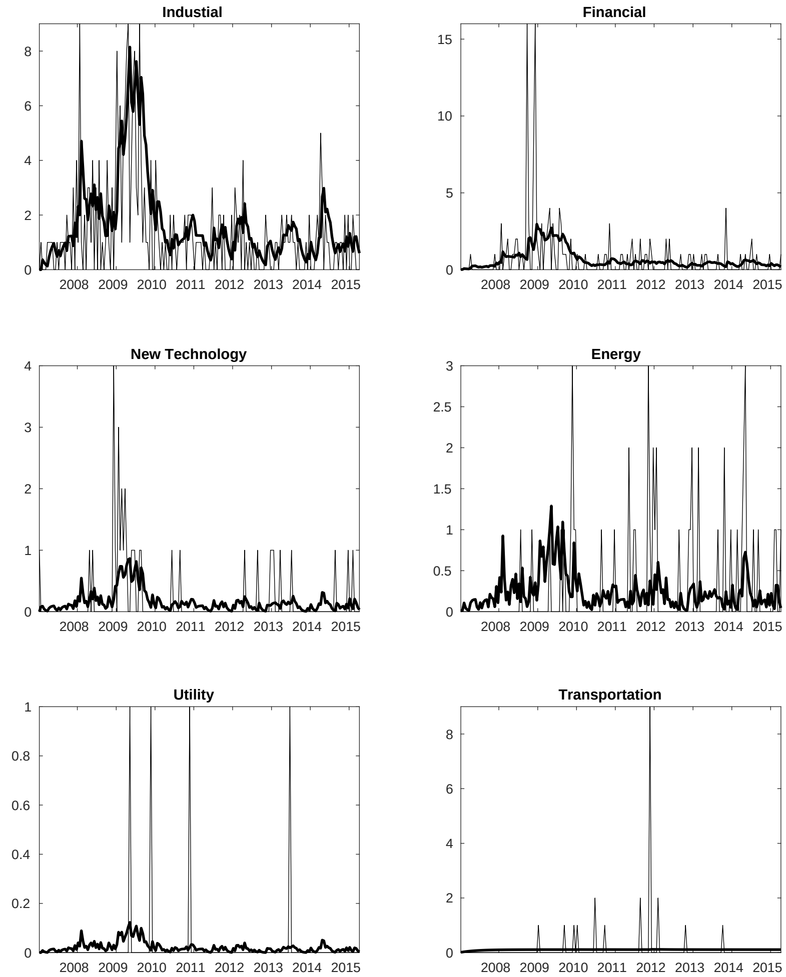

Figure A.6: Implied λs for Model 2, second period (2006-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

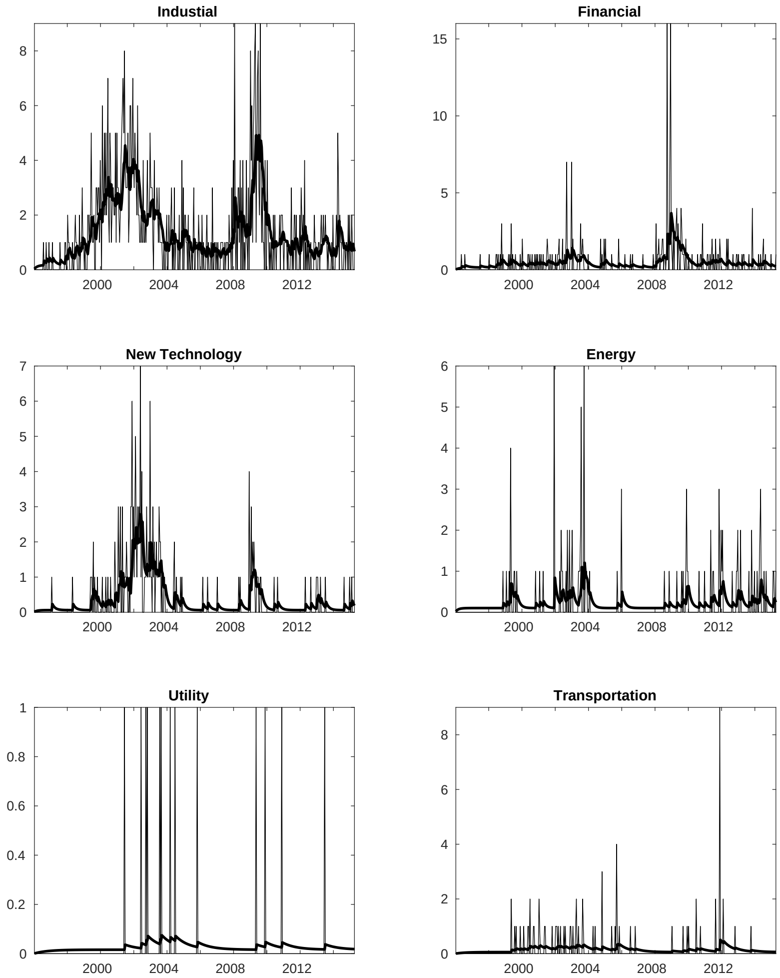

Figure A.7: Implied λs for Model 0, restricted to $\gamma = \delta = 0$, entire period (1996-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

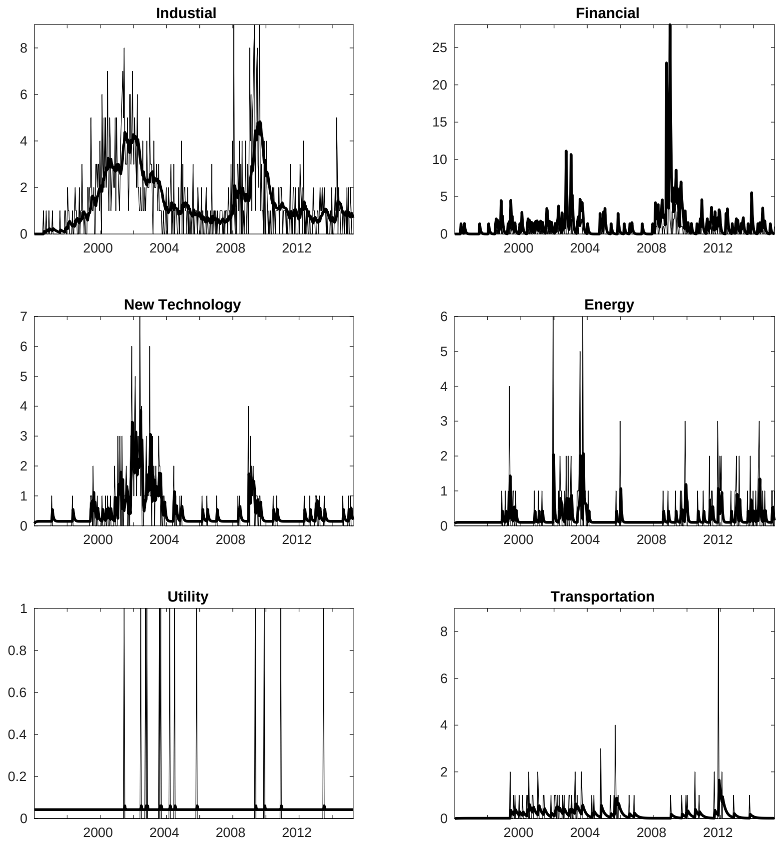

Figure A.8: Implied λs for Model 0, restricted to $\gamma = \delta = 0$, first period (1996-2005). Bold lines refer to the intensities and thin lines to the actual number of defaults.

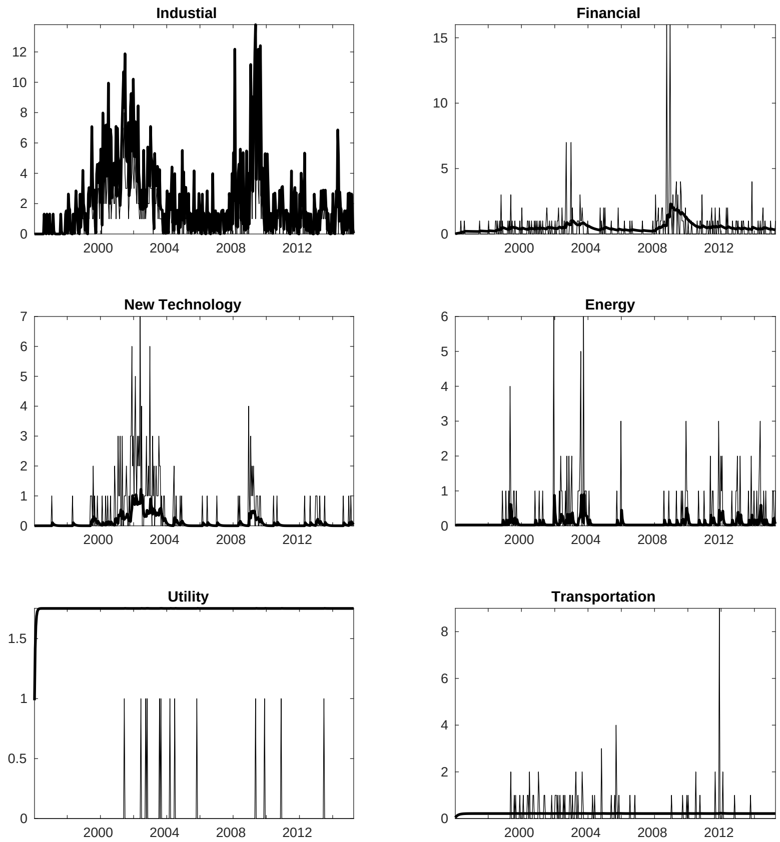

Figure A.9: Implied λs for Model 0, restricted to $\gamma = \delta = 0$, second period (2006-2015). Bold lines refer to the intensities and thin lines to the actual number of defaults.

Panel A.			*Entire period (1996-2015)*			
	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0341•	0.0231**	0.0130*	0.0227	0.0008	0.0041•
	(0.0183)	(0.0086)	(0.0059)	(0.0254)	(0.0012)	(0.0023)
a	0.1661***	0.1068***	0.1720***	0.1226•	0.0205•	0.0420***
	(0.0294)	(0.0240)	(0.0405)	(0.0628)	(0.0112)	(0.0124)
b	0.8032***	0.8441***	0.7863***	0.7783***	0.9493***	0.9282***
	(0.0353)	(0.0299)	(0.0496)	(0.1550)	(0.0416)	(0.0180)
logl	-1991.6037					
AIC	4019.2					
BIC	4093.7					
Panel B.			*First period (1996-2005)*			
	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0000	0.0000***	0.0742	0.0625**	0.0427**	0.0032
	(0.0000)	(0.0000)	(0.0703)	(0.0239)	(0.0142)	(0.0030)
a	0.1145***	1.3758***	0.3977**	0.3232***	0.0184	0.1707*
	(0.0209)	(0.0124)	(0.1243)	(0.0813)	(0.0314)	(0.0749)
b	0.8853***	0.4785***	0.5014*	0.3612*	0.0016	0.8128***
	(0.0209)	(0.0146)	(0.2031)	(0.1615)	(0.0182)	(0.0857)
logl	-1288.1807					
AIC	2612.4					
BIC	2676.7					
Panel C.			*Second period (2006-2015)*			
	IND	FIN	NTEC	ENE	UTI	TRA
ω	0.0000	0.0138	0.0005*	0.0134***	0.9864***	0.0472***
	(0.0000)	(0.0105)	(0.0002)	(0.0026)	(0.0760)	(0.0132)
a	1.3131***	0.0505**	0.1031***	0.1416***	0.0009	0.0020
	(0.0000)	(0.0162)	(0.0210)	(0.0332)	(0.2275)	(0.0461)
b	0.1649***	0.9240***	0.6698***	0.4140***	0.4369***	0.7823***
	(0.0000)	(0.0156)	(0.0468)	(0.1046)	(0.0079)	(0.0231)
γ	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(1.0000)
δ	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
logl	-11466.9748					
AIC	22969.9					
BIC	23029.2					

Table A.1: **Model 0, restricted to $\gamma = \delta = 0$, parameter estimates for the three considered time periods.** This table shows the main results from Equations (1) and (2). *IND*, *FIN*, *NTEC*, *ENE*, *UTI*, *TRA* refer to industrial, financial, new technology, energy, utility, and transportation sectors, respectively. The number of defaults are obtained with data from the FISD database provided by the Mergent, Inc., and financial, real and macroeconomic data are obtained from the FRED, the FED, the Investing and the Cboe web pages. Asymptotic standard errors are reported in parenthesis. The codes ***, **, * and • indicate statistical significance at 0.1%, 1%, 5% and 10% levels, respectively.