Relational herding in financial markets: Mortgage securitization and the Spanish banking crisis

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Abstract

Economic theories of financial contagion and herd behavior share important properties with social influence and diffusion models in sociology and organization studies. However, both theoretical models and empirical tests of financial herding largely ignore relational models of network influence and diffusion processes. In this paper, we use a network approach to study the growth of a new and ultimately destructive financial technology, mortgage-backed securities (MBS) in Spain. We test for social influence processes based on communicative, competitive and collaborative relations (as well as spatial proximity) using network autocorrelation models. Because the Spanish MBS market emerged de novo in the mid-1990s, we are able to observe the complete history of the market prior to the crisis, and use network measures that pre-date the market itself. Results show that Spanish savings banks tended to emulate the behavior of their historical competitors, but we find no evidence of communicative or collaborative diffusion processes. This result is robust to controlling for a variety of relational and bank-level properties and mitigates concern about confounding homophily effects typically found in diffusion studies.

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Economic theories of financial behavior increasingly acknowledge social dynamics variously described as herd behavior, cascades, contagion, epidemics and manias (Kindleberger and Aliber, 2011; Shiller, 2015). Economic models of these social dynamics share important commonalities with a broad class of social influence and diffusion models developed by sociologists, organization theorists, and economists (Burt, 1987; Marsden and Friedkin, 1993; Strang and Soule, 1998; Durlauf and Ioannides, 2010; Centola and Macy, 2007; Centola, 2018; Valente, 2005; Manski, 2000). The common core of these theories is that economic actors partially base their action on the behavior of others rather than make decisions in atomistic fashion. Such social influence processes generate feedback or 'bandwagon' dynamics capable of driving the diffusion of particular innovations, beliefs and behaviors. However, the theoretical and empirical literature on financial herding has become narrowly focused on models of temporal clustering of investment decisions, tending to lose sight of the specifically social — i.e. embedded (Granovetter, 1985) — character of these dynamics. While there are good methodological reasons for this emphasis, we argue that research on the social dynamics of financial markets would benefit from drawing on insights from the social influence and diffusion literatures, particularly network approaches. In particular, we show that a relational herding process operating through competitive channels characterizes the dynamics of expansion in the financial market we study.

We test this social-relational model of financial action in the context of the emergence and crisis of a market for mortgage-backed securities (MBS) among Spanish savings banks. Securitization is the practice of of bundling financial assets (such as residential mortgages), with their associated risks and flows of payments, for resale to investors. There is a growing economic sociology literature on this technology (Goldstein and Fligstein, 2017; MacKenzie, 2011; Quinn, 2019), reflecting its status as a core institution of real estate markets. Like the United States and several other countries, Spain experienced a boom-bust cycle in the housing market (c. 1995–2008) in which mortgage securitization played a central role. Understanding why banks and other financial actors rapidly and intensively adopted a financial technology that proved self-destructive in the medium term is a fertile question for economic sociology, a subfield that emphasizes the limits to economic rationality and efficiency. A key feature of the Spanish case provides an important degree of empirical leverage in testing network theories of influence. MBS was a new financial technology in Spain, particularly among savings banks; the first MBS issuance occurred in 1993, and substantial volumes began only in 2000. Thus, Spain provides the opportunity to observe the de novo emergence and collapse of a financial market. Methodologically, this enables us to measure network structures *before* the existence of the financial technology in question, mitigating concerns about the confounding effects of homophily typically present in social influence studies (Shalizi and Thomas, 2011).

Our empirical analysis draws on an original bank-level dataset that includes information on every mortgage securitization vehicle since the inception of the market, in order to examine whether social influence processes led savings banks to issue larger — ultimately unsustainable — volumes of mortgage backed securities. We first show that the volume of residential MBS issuance is strongly associated with indicators of bank distress at the outset of the crisis, providing evidence that securitization was a critical factor in the collapse of the Spanish savings banks. We then estimate network autocorrelation models capturing social influence processes occurring between banks. Our main finding is that competitive relations between banks were a significant channel of social influence, driving up bank leverage in the form of mortgage backed securities. Simply put, the banks that issued the largest volume of mortgage backed securities (relative to their overall size) were embedded in competitive relations with other intensive issuers. This effect is robust to a variety of specifications, though we show that it requires disentangling competitive relations from geographical proximity. Our results are thus consistent with previous diffusion studies showing that competitive relations are a key channel of social influence (Burt, 1987; Bothner, 2003). Going beyond these studies, however, we examine multiple, substantively distinct network measures, showing that competition rather than communication, cooperation or spatial proximity were central to the influence process. Furthermore, we disaggregate influence processes within the Spanish MBS market, showing that this competition-driven influence process occurred within the most novel and risky market segments — those that drove the bulk of the MBS issuance among banks that collapsed after 2009. This evidence supports the view that social influence dynamics played a key role in driving the financial behavior that ultimately led to the destruction of the Spanish savings bank sector.

The next section develops the implications of social influence models for the financial herding literature, and develops hypotheses about three distinct influence channels. We then introduce key features of the Spanish case, particularly the three major forms of mortgage securitization which provide empirical leverage for our analysis. After introducing our new dataset and methodology, the following section provides evidence that mortgage securitization levels are associated with bank distress at the outset of the crisis, and that an influence processes operating through competitive channels was a primary driver of the accumulation of securititized mortgage portfolios.

1 From financial herding to social influence process

Many economists (Brunnermeier, 2001; Kindleberger and Aliber, 2011; Shleifer, 2000; Shiller, 2015) argue that financial crises result from endogenous dynamics that result in the formation of price 'bubbles' (unsustainable price increases followed by a crash) or more generally periods of rapid, unsustainable increases in the value of particular financial assets or asset classes (for a contrary view, see Fama, 2014). With important variations, this literature describes a simple, general model of boom-bust financial cycles stressing the endogenous instability of financial markets. According to this model, a new (or renascent) investment opportunity, commodity or financial asset class first attracts attention from early investors. Examples include Dutch tulips, technology stocks, real estate, and mortgage-backed securities. Novelty is often a key catalyst: the existence of a new object of investment or technology of risk management inspires belief in a new domain of profit opportunities. Observing the returns of early investors, others then begin to emulate their behavior. Still others copy these secondary entrants. At the peak of the boom, economic actors generate narratives that rationalize rapid appreciation, such as the 'new economy' stories that accompanied the technology stock boom of the 1990s, or beliefs about the the ability of structured finance to accurately price and distribute the risks of mortgage lending. These narratives inspire 'irrational exuberance' (Shiller, 2015), in which actors become convinced that price increases will continue indefinitely. Asset prices become un-moored from long-run values. Eventually, asset inflation becomes unsustainble, initiating a financial crash.

If something like this model is correct, then understanding the micro-level processes that generate these macro-level dynamics is an important task. Scholars have also offered theories of these processes, invoking notions of herding, mob psychology, groupthink, fads, and crowd behavior (Kindleberger and Aliber, 2011; Shiller, 2015; Akerlof and Shiller, 2009; Adler and Adler, 1984). Keynes (1936) famously described investment as a beauty contest: an investor may purchase assets because she believes that others believe these assets are valuable, rather than because she herself believes they are valuable. This role for "expectations of expectations" implies that the social and informational channels that financial market participants use to develop their beliefs about other market participants' behavior can have an important influence over economic action. Such approaches are central to the field of behavioral finance: in a seminal article, Shiller (1984) argued that fads and fashions are endemic to financial markets, suggesting that group conformity and word-of-mouth information diffusion create volatility in the stock market. More recently, this literature has centered on the concept of herd behavior. Informally, herding describes a collective rush to invest in particular assets or asset classes characteristic of a booming market. Formally, this literature defines financial herding as behavior in which individual market participants disregard private information and instead imitate the behavior of others (Bikhchandani and Sharma, 2001; Cipriani and Guarino, 2014; Brunnermeier, 2001).

Financial herding is a special case of a much broader class of social influence and diffusion models, on which there is a large literature in sociology and organizational studies (for a review, see Strang and Soule, 1998). A seminal early example is the threshold model formulated by Granovetter (1978): in this model, adoption of a particular behavior depends on the proportion of relevant peers who have already adopted the behavior. For example, an individual's decision to join a social movement is likely to depend on how the proportion of their peers who have already joined. Building the classic work of Merton (1968) on reference groups, this approach leads analysts to focus on the groups or networks that constitute a focal actor's peers. Thus, both economists and sociologists deploy models in which individual behavior depends on the average behavior within the groups to which individuals belong (Fligstein, 1985; Durlauf and Ioannides, 2010). A parallel approach developed within the social networks literature is to model the action of a focal actor as a function of the behavior of other actors and the social relations between them (Marsden and Friedkin, 1993; Burt, 1987; Bothner, 2003; Davis, 1991; Davis and Greve, 1997; Strang and Soule, 1998). Rather than relying on average group behavior, this approach takes into account the behavior of all relevant peers, weighted by a measure of tie strength or social proximity. Both group and network influence processes can generate diffusion processes, in which innovations and novel practices spread throughout a target population of adopters.

Despite this ostensible convergence between financial economics and organizational sociology, however, there is a key difference. Contemporary financial herding models are largely asocial or "disembedded." The theoretical literature focuses primarily on the cognitive microfoundations and informational properties of markets that could give rise to herding dynamics (reviews include Bikhchandani and Sharma, 2001; Brunnermeier, 2001). Theoretical models emphasize rational herding in which influence arises from information externalities (Banerjee, 1992) or reputational effects (Scharfstein and Stein, 1990).[1] These models express a rather different (though not incompatible) insight than the social influence models just discussed. In terms introduced by Strang and Tuma (1993: 615), behavioral finance models assume assume spatial homogeneity: "all members of the population have the same chance of affecting and being affected by each other." "Spatial" here refers to both geographical and social (e.g. network) distance. This approach to herding is asocial (or disembedded) in the sense that mimetic behavior occurs with reference to a generic market (reflected, for instance, in the stream of prices for a particular asset)[2] rather than particular reference groups or network neighbors. In this sense, while these models have many virtues, they tend to lose sight of the range of social processes that might drive financial market behavior. More concretely, one key limitation of these models is that they provide no leverage for analyzing the heterogeneity of social influence processes: that is, why some actors adopt innovations more quickly or more intensively than others.

Similarly, most recent empirical tests of financial herding take the form of statistical search for non-random temporal "clustering" of investment decisions. For example, Lakonishok et al (1992) introduced a measure of the temporal correlation of investment decisions, relative to the expected correlation if investment managers are independent (for a review, see Bikhchandani and Sharma, 2001). However, this approach cannot eliminate the possibility that temporal clustering is due to common reactions to new information (Cipriani and Guarino, 2014: 225). More sophisticated approaches seek to identify herding either through laboratory experiments or via structural models relying on high-resolution data. Both approaches identify herding with reactions to overall price trends in the market (despite private information); for example, herding occurs when a trader "[buys] after the price has risen or [sells] after the price has fallen" despite private information (Cipriani and Guarino, 2014: 232). Such tests focus entirely on temporal dynamics, rather than seek to identify heterogenous social influence processes.[3] Causal identifiability is a major motivation of these methods.

A related issue is that the formal economics literature is almost entirely focused on stock markets. These markets have a number of specific features, including centralization on a small number exchanges and the widespread availability real-time flows of rich quantitative data. In such markets, investors can 'watch the market' (and thus become susceptible to herd dynamics) based solely on interaction with a technical data interface. Drawing on the social studies of finance literature (MacKenzie, 2009), we can term such social dynamics socio-technical herding: social influence processes mediated by a technological data infrastructure which automatically aggregates information about collective market behavior in real time. These models are less useful for decentralized, slower-moving markets with less rich data streams. For example, in real estate markets information is (comparatively) scarce and available with a lag. Nevertheless, Shiller (2015) and others suggest that herding dynamics may be common in real estate and mortgage credit markets.

Thus, while recent literature on herding has the virtue of analytical clarity and (in principle) identifiability, it abandons some of the insights that originally animated social models of financial behavior in the economics literature. Shiller (1984) bases his discussion of social dynamics on processes of group conformity and word-of-mouth information transmission, rather than atomistic investors watching a market index. Like the sociological diffusion literature, this suggests that herd behavior is financial action driven by processes of mutual influence. Methodologically, this suggests that in addition to the search for *temporal* clustering of investment decisions in the economics literature, empirical approaches should also test for *network* clustering in financial behavior. Sociological diffusion theory implies that actors are differentially likely to adopt technologies or behaviors when they are embedded in networks of social relations. We may thus distinguish between socio-technical and relational herding. Relational herding implies that financial actors adopt behaviors that are similar to network neighbors defined on some underlying relational structure. We turn to the content of this structure in the next subsection.

1.1 Channels of relational herding

The diffusion literature suggests several distinctive network channels or mechanisms of social influence that can drive diffusion processes. We identify three such channels: relations of communication, competition, and cooperation. These channels represent variations in substantive network content, social process, and motivations for action. Our specification of these channels draws on previous efforts to synthesize the literature on social influence and diffusion (Strang and Soule, 1998; Marsden and Friedkin, 1993; DiMaggio and Garip, 2012; Lieberman and Asaba, 2006). However, our typology of diffusion mechanisms differs from these account because we focus on the distinct social processes implied by influence and diffusion through networks with different substantive content, rather than formal properties of networks.

Dyadic relationships based on communication and information flow are commonly suggested avenues of diffusion. In the simplest cases, in the absence of 'broadcast' media for disseminating information, the spread of novel practices may require private, dyadic transmission of information, such as through face-to-face conversation. Even if some broadcast information is available, novel technologies and other innovations often gain in value if more detailed private information is available (DiMaggio and Garip, 2012). For example, information about how to best use a technology may travel through dyadic channels, even if information about the existence of the technology as such is generally available. Communicative channels of diffusion encompass both "cohesion" and "weak ties" theories (Strang and Soule, 1998: 272–273); these theories differ on the character of relevant social ties rather than the social process of diffusion.

One of the leading examples in the literature is diffusion through corporate board interlocks (Davis, 1991; Davis and Greve, 1997). Corporate interlocks occur when directors sit on the boards of multiple firms, thus creating an inter-organizational network. The network of board overlaps provides a key channel of sociability and communication; interlocks are "conduits of information flows…transmitting social norms, values and strategies" (Davis 1991, c.f. Burt 1987). In other contexts, political ties — such as organizational interlocks based on party-affiliated directors — are important channels for information available to political elites and relevant to business decision-making (Stark and Vedres, 2012). However, we are not aware of any studies that examine political interlocks as a channel for diffusion, as we describe below.

Competitive relations are a theoretically distinct channel of diffusion (Burt, 1987; Abrahamson and Rosenkopf, 1993; Bothner, 2003). Whereas relations of communication spread information about innovations, competitive relations are not generally characterized by intense information flows. Competitors may avoid communication altogether, disclose information selectively, or actively dissemble in order to undermine competitive threats. Thus, while competitors may communicate, the mechanisms underlying competitive diffusion processes are distinct from those involved in communicative diffusion. Competing units emulate one another because they "[use] one another to evaluate their relative adequacy" (Burt, 1987: 1291) or "in order to avoid falling behind" (Strang and Soule, 1998: 274). In other words, competitive mimicry emerges because firms monitor peer groups — defined as the set of other firms with which they compete — in order to devise strategies for effective action.

The literature tends to associate competitive diffusion processes with structural equivalence measures, that is, similarities in patterns of relationships to third parties (Burt, 1987; Bothner, 2003). An early debate treated cohesion (based on communication, as we stress above) and structural equivalence as competing network models (Burt, 1987). Here, we emphasize that the main contrast between these perspectives is the underlying mechanism driving diffusion, rather than structural equivalence per se. Structural equivalence is an indirect measure of competition reliant on the assumption that actors sharing ties to similar sets of alters sit in relations of competition. The validity of this assumption depends on the substantive nature of actors and ties, as well as the available data; in this paper, our data permits a more direct approach to measuring competition.

A less explored channel of diffusion are relations of cooperation (Wang and Soule, 2012). Cooperative relationships are based on formal or informal agreements to act jointly, ranging from informal ties based on repeated transactions to joint ventures, strategic partnerships and alliances, and in the extreme, collusion and cartels (Powell, 1990). Cooperative ties of course involve communication, but go beyond information sharing insofar as they involve various degrees of exchange and collaboration. Cooperative ties are clearly distinct from relations of competition, because payoffs are likely to be positively rather than negatively correlated. This distinct relational basis suggests a different underlying logic of diffusion. Whereas communicative ties often disseminate information that increases the value of adopting an innovation from the standpoint of later adopters, collaborative relations may involve processes in which later adoptions benefit early adopters. Such processes may occur in situations analogous to the classic network externalities of communication technologies (e.g. the fax machine): early investors have incentives to encourage further adoptions because these increase the value of existing investments. This suggests an instrumental, persuasion-based process of diffusion in which early adopters actively encourage later adoptions, rather than the purely information-based process driven by communicative ties. For example, in the diffusion of protest tactics between social movements (Wang and Soule, 2012), organizations do more than share information about tactics: they actively collaborate in joint action based on those tactics. One social movement seeks collaborators, and encourages these collaborators to adopt a particular tactic, because the strategic interaction is more likely to succeed if a network of organizations acts collectively. In such instances, a diffusion process may be a deliberate result of strategic action, rather than an unintended byproduct of information flow. The spread of mortgage securitization in Spanish savings banks may be such a process, because (as we explain in greater detail below) many securitization deals involved consortia of small banks working together.

In summary, relational herding refers to a social influence process in which market actors emulate the behavior of specified peers, rather than a generic market captured in a data flow. Communicative, competition and collaborative networks represent different aspects of relational content corresponding to distinct social processes of influence. In what follows, we introduce measures of these distinct network forms and test their role in the expansion of MBS issuance in Spain.

2 The Spanish case

While there is substantial research on the boom-bust housing cycle that triggered the global financial crisis of 2007–2009, much of this work has focused on the United States. With its liberal political economy and large, loosely regulated financial sector, the U.S. has a number of unique features which make conclusions from this case difficult to extrapolate to other countries. Thus, the dynamics of housing finance cycles are worth exploring outside the US context. As noted above, Spain experienced a dramatic boom-bust cycle in the housing market that rivaled the US bubble. Spanish housing price inflation in Spain was comparable to the United States, while the post-crisis collapse in housing prices exceeded price declines in the US and UK. Price increases were accompanied by rapid credit expansion; the rate of credit growth in Spain increased from around 15% in the late 1990s to a peak above 25% in 2006 (Fernández de Lis and García Herrero, 2008: 16). The flip side of credit growth was a rapidly rising level of household debt; while aggregate household debt (composed overwhelmingly of mortgage debt) stood at 82% of gross disposable income in 2000, by 2007 household debt was 135% of income, a level comparable to the U.S.[4] Once the boom phase of the housing cycle had run its course, this rising debt proved unsustainable: the percentage of non-performing loans in the banking sector as a whole increased from 1% to a peak of 13% in 2013.

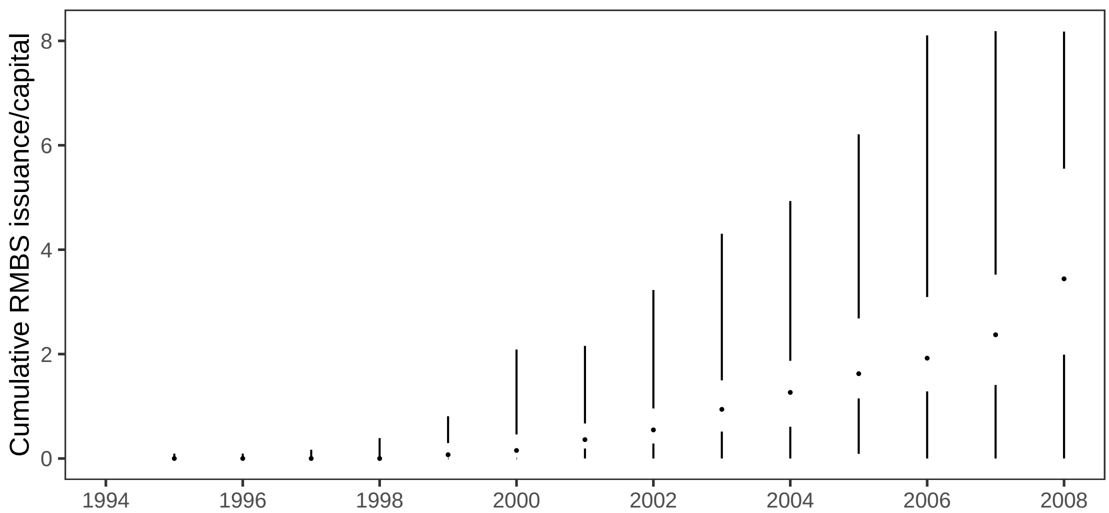
The Spanish financial crisis centered on the quasi-public, non-profit oriented savings bank sector, rather than private investment banks and specialized mortgage lenders. Prior to the crisis, the two main components of the Spanish financial sector were large, internationally diversified commercial banks (such as Santander and BBVA) and savings banks. While commercial banks weathered the crisis relatively well (with a few exceptions), the savings bank sector suffered systematic collapse beginning in 2009. This sector consisted of about fifty small and mid-sized banks specialized in retail activities, such as extending loans to homeowners and small businesses. Two larger savings banks La Caixa (based in Barcelona) and Caja Madrid led the sector, with more than 150 billion euros in total assets; the majority of savings banks were much smaller, with less than 50 billion in assets. In the legal regime prevailing prior to the crisis, savings banks were formally private foundations which distributed profits to local communities via their philanthropic arms (*obras sociales*). The sector had its origins in religious thrift organizations (*montes de piedad*), dating to the 18th century; some savings banks remained controlled by the Catholic church, while the majority were founded and controlled by local and regional governments. Because of the close political connections of these financial entities, post-crisis debate in Spain has focused on political influence on lending practices as possible corruption, particularly related to real estate developers (Cuñat and Garicano, 2009; Lavezzolo, 2014; de Barroon Arniches, 2012).

While the savings bank sector suffered a generalized crisis, variation in outcomes across institutions provides important leverage for studying the pre-crisis behavior of these organizations. Though the majority of the savings banks in existence before the crisis received direct or indirect bailouts between 2009 and 2012, several banks avoided relying on public support. In particular, Barcelona-based La Caixa, three Basque savings banks, and the Andalusian Unicaja avoided direct bailouts entirely. Other banks received support as a part of their absorption of other, insolvent entities, which appears to indicate a greater structural soundness during the crisis. Thus, as argued above, participation in the behavior that instigates financial crises is heterogeneous; this heterogeneity provides an important degree of leverage in explaining the housing boom and crisis in Spain.

An important contributing factor in the crisis, as we show below, was the creation of a market for mortgage backed-securities. In the early 1980s the Spanish government began to encourage the expansion of the mortgage market; reforms facilitated bank access to capital markets (Levenfeld and Sanchez, 1988). Subsequently, in the early 1990s an additional reform introduced modern mortgage-based securities (*Fondos de titulizacion hipotecaria*), enabling Spanish banks to access larger pools of capital, particularly outside Spain (Catarineu and Pérez, 2008; Alberdi, 1997).

The first Spanish MBS issuance occurred in 1993, but volume remained limited through the end of the 1990s, accelerating rapidly around 2000. Outside of the UK, Spain emerged as one of the largest participants in the European securitization market in terms of nominal value. According to ECB estimates, mortgage backed securities amounted to more than 30% of outstanding mortgage credit in Spain, the highest level in the eurozone in relative terms (European Central Bank, 2009). Combined with conventional covered bond funding, total capital market funding of mortgage lending in Spain reached 45% of mortgage credit, substantially higher than countries such as the

Figure 1: Mortgage securitization: trend and variation



Netherlands, Ireland and Portugal, which also saw substantial credit-fueled housing booms. The growth of the MBS market allowed Spanish banks to access pools of foreign capital; by 2007, "66% of securitization bonds issued by Spanish institutions were held by foreign investors" (European Central Bank, 2009).

Figure 1 illustrates the growth and variability of mortgage securitization in the savings bank sector (see below for a description of the data). Cumulative issuance of residential MBS began to trend upwards as a percentage of bank capital around the beginning of the 2000s. From a total securitized liability close to zero for most banks in the mid–1990s (since the market was non-existent prior to 1993); the average savings bank had cumulatively issued mortgage backed securities equal to the value of its capital by 2005. This average value continued to rise for three more years until the peak of the boom; at the same time, the distribution became more dispersed and increasingly skewed, as a few banks took on extreme levels of leverage relative to their capital.

There are several reasons to study the role of securitization in the Spanish financial crisis. Most simply, as noted Spain was both one of the biggest issuers of MBS in continental Europe in relative terms and experienced a substantial housing cycle and crisis. Second, although research to date is limited, a few studies suggest connections between mortgage securitization, credit expansion, and the deterioration of credit quality. Otero González et al. (2013) find that MBS issuance prior to the crisis is a significant indicator of bank insolvency, credit risk, and non-performing loans in the banking sector as a whole, and Carbó-Valverde et al. (2012) show that securitization levels influence loan growth rates, which in turn are related to non-performing loans and ratings downgrades of mortgage backed securities. Because neither of these studies focuses specifically on the savings bank sector (as noted, the key locus of the crisis), we present simple cross-sectional analyses showing that growth in MBS issuance is associated with non-performing loans in the sector during the crisis.

However, the argument that mortgage securitization played a central enabling role in the crisis conflicts with many previous existing accounts of the Spanish mortgage securitization market (Catarineu and Pérez, 2008; Fernández de Lis and García Herrero, 2008; Martín Martín, 2014). These sources emphasize that the Spanish mortgage securitization differed substantially from its US counterpart, arguing that the system was fundamentally conservative or "plain vanilla." This evaluation is based primarily on the absence of an 'originate to distribute' model and the relative simplicity of fund structures. In particular, regulation and accounting rules substantially prevented Spanish banks from moving risks off-balance sheet; rather, securitization primarily played a liquidity or funding role, rather than transferring risk (European Central Bank, 2009: 49). On this view, regulations that tended to keep mortgages on balance sheet are fundamentally safer than as system, as in the US, focused on risk-transfer mechanisms that supposedly create perverse incentives. This view is challenged by the fact that many US MBS issuers in fact retained large stakes in the market (Goldstein and Fligstein, 2017; Acharya et al., 2013). In light of this evidence, the fact that most Spanish MBS remained on balance sheet implies the opposite: the concentration of risks within banks may have been one of the fundamental sources of instability.

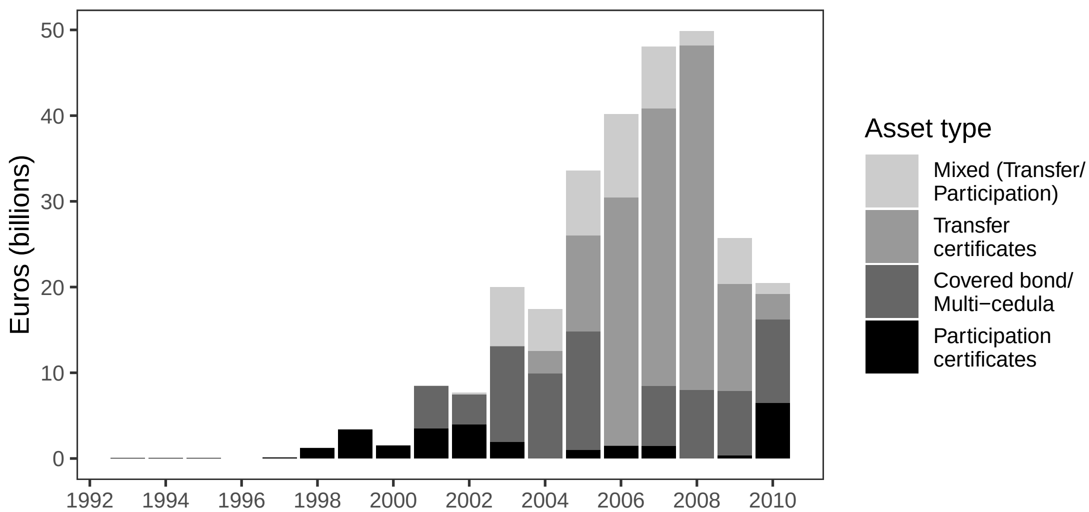
The endogenous instability view of financial markets introduced above implies that financial markets are intrinsically crisis-prone. Rather than the outcome of particular institutional configurations — whether the 'originate to distribute' model, vertical integration in the securitization industry (Goldstein and Fligstein, 2017), or political factors — crises result from the dynamics of finance itself. While testing this broad view of financial crises is beyond the scope of this paper, we seek to study one aspect of it, namely the relational herding hypothesis introduced above. In order to do so, we leverage variation in the character of securitization over time. An important aspect of the endogenous instability view is that novelty plays a central role in boom-bust cycles, insofar as financial assets or technologies perceived as new in a particular context appear to more often trigger waves of financial 'exuberance' (Shiller, 2015). Because of this, the changing form of mortgage securitization over time is a useful source of empirical variation in the Spanish case.

The earliest mortgage-backed securities issued in Spain (beginning in 1993) were pools of assets called mortgage share certificates (*participaciones hipotecarias*) similar to the mortgage participation certificates (also known as pass-through securities) issued by Freddie Mac in the US (Quinn, 2019). Spanish legislation required the underlying mortgages to conform with relatively strict conditions, such as loan-to-value limits (Catarineu and Pérez, 2008; Arranz Pumar, 2009). As figure 2 shows, these early securitization instruments played a modest role in the Spanish market (relative to the total growth in MBS issuance) during the boom years between roughly 2000 and 2007 (see below for a description of the dataset). Rather, most growth in MBS issuance involved two alternative types of underlying assets: covered bonds (*cedulas hipotecarias*) and mortgage transfer certificates (*certificados de transmision de hipoteca*).

Covered bonds are assets backed by a bank's entire mortgage portfolio (subject to certain eligibility rules) rather than a specific pool of mortgages; as such covered bond financing is usually considered an alternative to securitization as such. However, in Spain a second form of covered bond known as multi-issuer cedulas created pools of covered bonds issued by consortia of smaller banks. These transactions had important similarities to the collateralized debt obligations (CDOs) central to the US crisis, but with the mortgages (and risks) remaining on-balance sheet (Kaminska, 2009). Second, mortgage transfer certificates were a legal innovation introduced in 2002 in response to industry pressure to facilitate the securitization of riskier "non-conforming" mortgages (to borrow US terminology), such as those with higher loan-to-value ratios. In addition, some funds pooled both conforming (mortgage share certificates) and non-conforming (transfer certificates).

In our analysis, we leverage this variation in the assets underlying Spanish securitization funds in order to better understand the role of relational herding in the Spanish mortgage securitization boom. If indeed an inter-bank social influence process was a significant factor driving the boom

Figure 2: Spanish mortgage securitization issuance by asset type

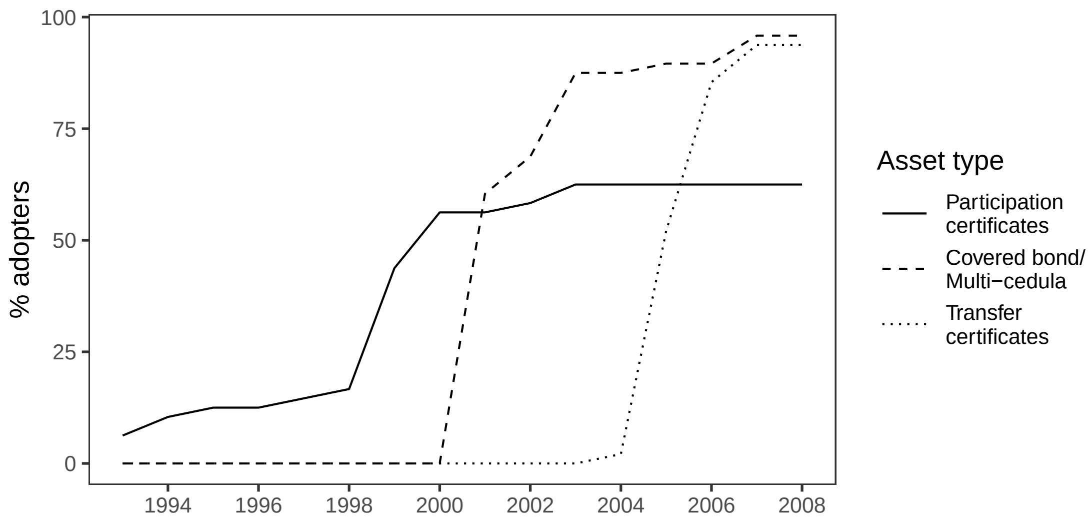


(and crisis), we expect this influence process to be strongest in novel and risky asset categories. This is consistent with the endogenous instability view described above. As figure 2 shows, growth in mortgage securitization in the savings banks sector was concentrated in markets for covered bond and non-conforming mortgages. Further, these securitization technologies were absolute novelties that emerged concurrently with the boom and spread almost instantaneously. This is illustrated in figure 3,which shows the diffusion dynamics for each type of securitization fund. Both covered bond and non-conforming mortgage securitizations spread extremely rapidly (within 2–3 years) following their introduction. In contrast, 'traditional' mortgage participation securitizations did not reach more than 50% of savings banks until 2000 (nine years after the first fund was launched in 2001). These patterns are consistent with endogenous instability: rapid expansion of a new financial technology and asset type, which (ex post) turned out to be unsustainable.

3 Data and methods

In the social networks literature, the network autocorrelation model is a classic method for studying diffusion and social influence (Doreian et al., 1984; Leenders, 2002; Mizruchi et al., 2006; Valente,

Figure 3: Spanish mortgage securitization diffusion by asset type



2005). This model postulates that the behavior of an actor i depends on the behavior of alters j_n, weighted by the intensity of the relationship between i and j. More formally:

$$y = \rho W y + \beta x + \varepsilon$$

where W is a matrix of weights representing proximities based on geography, social networks, or other similarities. For example, if y is the volume of MBS issued by each savings bank, the MBS issuance of bank i is a function of the issuance of each other bank j, weighted by the relationship between i and j. According to this model, if i and j have no relationship ($w_{ij} = 0$) then j's behavior y_j has no influence on i (because $w_{ij}y_j = 0$). On the other hand, if i and j have a strong relationship (for example, if $w_{ij} = 1$), then j's behavior has a strong influence on i (because in this case $w_{ij}y_j = y_j$). This model is formally equivalent to the spatial autocorrelation model (Anselin, 2002) in which the weight matrix is generally defined by the geographical proximity between units; the key difference lies in whether the weights reflect geographical or social proximity. The critical assumption of this model is therefore the definition of the weight matrix (Leenders, 2002).[5]

Our main variable of interest is each savings banks' cumulative MBS issuance, standardized by the bank's capital.[6] As such, we focus on the *intensity* of adoption of this financial practice rather than the timing of adoption, which is often the focus of diffusion studies. Nearly all Spanish savings banks had entered the MBS market by 2002, but as figure 1 shows, there is a wide range of variation in the intensity of MBS issuance. We view this variation in intensity as intrinsically more interesting than the timing of adoption, in particular because (as we show below) it is linked to bank distress at the outset of the crisis. Conversely, we find no evidence that the timing of adoption is linked to bank distress, and the timing of adoption is loosely linked with intensity of adoption at the peak of the cycle. In our models below, we *control for* the timing of market entry, rather than treat this as our dependent variable, showing that while the timing of diffusion is associated with intensity, our social influence findings are not undermined by this effect. We also estimated a series of hazard models testing whether social influence effects influence the timing of adoption, but did not find any evidence of such effects.

We calculated annual and cumulative MBS issuance (1995–2008) at the bank level by determining the value of securitized assets from issuance documents obtained from the Bank of Spain, the Spanish National Bond Market Commission (CNMV), and six private firms specialized in managing the securitization funds (special-purpose vehicles) at the core of Spanish mortgage backed securities. Many Spanish MBS were issued by a consortium of savings banks (that is, several smaller banks would pool mortgage assets in a single fund which provided the basis for an issuance of mortgage-backed securities). We obtained the issuance documents (prospectuses) of all Spanish mortgage backed securities through the inception of this market through 2009 and recorded the nominal value of the underlying mortgage assets contributed by each savings bank to each special-purpose vehicle. By aggregating across securitization funds, this permits calculation of the annual financing and total cumulative financing of mortgage lending through MBS by each savings bank. We matched these MBS issuance data to balance sheet information for each bank provide data on assets and capital in order to standardize our measures by bank size.[7]

As noted above, we seek to assess communicative, competitive and collaborative relations as channels of social influence. The leading approach to defining inter-organizational communicative relations is the interlocking directorates approach. However, because board membership in Spanish savings was composed of local stakeholders, there are no overlaps in board memberships between banks.[8] However, the partisan network connecting banks controlled by the same political parties is a relevant analogue to interlocking directorates in this context. To the extent that elected politicians sought to use the savings banks to boost political support in their home regions, and to the extent that MBS issuance was a necessary enabling condition for increasing the flow of credit, we expect to observe autocorrelation in the partisan interbank network. We construct this partisan network by matching banks to *comunidades autonomas* (CA) based on the location of bank headquarters, and computing the proportion of years in which dyads' respective CA were controlled by the same political party over an eight-year period (i.e. the length of two electoral cycles). This is and the other relational matrices described below are all row-standardized in our autocorrelation models, following conventional practice.

As noted above, the diffusion literature typically conceptualizes competitive relations in terms of structural equivalence. In this paper we adopt a more direct approach. Drawing on research into the socio-spatial embeddedness of firms' activities, also known as multi-market contact (e.g. Haveman and Nonnemaker, 2000), we measure competitive relations between savings banks using data on the provincial[9] location of bank branches. Branch locations provide a substantively important indicator of competitive relations between savings banks, particularly with regard to mortgage lending activity, because housing is an intrinsically geographically-specific asset and because retail banking activities depend on customers' easy access to bank locations (particularly in Spain at this time). We thus assume that the impact of a province on a bank's self-perceived performance is proportional to the number (or percentage) of branches located in that province.[10]

A simple measure of multi-market contact is simply the number of provinces in which banks i and j both have branches. However, this specification disregards two key considerations. First, big banks likely represent a greater competitive threat to small banks than vice versa (Bothner, 2003). Second, a simple count of competitive provinces disregards the fact that some provinces are central to a bank's business strategy, while others are relatively important. Thus, our preferred measure of competitive relations is a sum of the number of provinces in which each pair of banks competes, in which each province is weighted by its salience to a focal bank (the proportion of that bank's branches located in the relevant province). We also weight this measure by the relative size of the banks, with size measured as the total number of branches. In robustness checks, we consider alternative definitions based on the raw count, province salience only weighted count, and relative size only weighted count. Our base models define these measures in 1995 in order to limit the possibility of endogeneity of competitive relations (e.g. due to banks selecting into high-growth areas). We discuss this issue in more detail below. Our third channel of potential interbank influence consists of collaborative ties. One relevant form of collaboration is the consortium model of MBS issuance mentioned above. Many MBS were jointly issued by groups of smaller savings banks. This model provides an obvious motivation for savings banks to seek the involvement of other banks: gathering a significant pool of mortgage issuers may have been necessary to generate the critical mass required to issue a bond. In some cases, banks may have been motivated to assemble a geographically diverse portfolio of mortgages, requiring the involvement of a range of banks, as an inducement to investors. In order to define collaborative networks based on these intuitions, we take advantage of the fund-level MBS data described above. Thus, we define collaborative ties as the number of joint issuances (funds) in which bank dyads participated. We also standardize this measure by relative size using the branch-based measure described above. If active collaboration between banks was a key channel for the diffusion of MBS, we would expect this joint issuance network to be a an important channel for this influence.

In addition to these three theoretically motivated channels for diffusion, in this paper we also pay careful attention to geographical proximity for several reasons. Diffusion research has long used spatial proximity as a proxy for networks. For example, White (2002) associated geographic proximity with competition, and Hedström (1994) conceptualized spatial proximity as a key force driving the formation of social networks responsible for information flow. Furthermore, economics literature examining peer effects in financial markets (Brown et al., 2008; Kaustia and Knüpfer, 2012) almost exclusively uses geography as a proxy for social contact. In this paper, we seek to contribute to the diffusion literature by disentangling the effects of geographical space from networks of communication, competition and collaboration. Because geography is indeterminate with respect to network content, sheer proximity does not allow analysts to identify a particular social process driving diffusion. Moreover, spatial proximity as a proxy for networks may be particularly susceptible to confounding common shocks with influence processes. Because social processes are typically clustered in space (for reasons other than influence), a purely geographical specification may mistake spatially uneven processes for social influence. In our case, the Spanish real estate and mortgage boom was clearly unevenly spatially distributed, with price increases concentrated along the Mediterranean coastline and a few other locations. While spatial proximity is not the same as geographical position, they are intrinsically related. Thus, we explore the relationship between geographical proximity, locale and substantively specific networks in order to establish that apparent network effects are not spurious effects of geographical space. We define geographical distance as the inverse log distance (in kilometers) between banks' headquarter cities (rescaled to set the maximum distance to one). The correlation between this geographical weights matrix and the competitive weights is moderate, showing that the competitive weights are not simply a proxy for geographical proximity.

Our social influence models include a number of bank and province-level covariates to control for other factors. In one of the few papers to examine variation across the Spanish savings bank sector, Cuñat and Garicano (2009) found that indicators of bank human capital and financial expertise predicted credit growth and non-performing loans. We use executive turnover as a proxy for these human capital variables.[11] Political lending accounts of the crisis suggest that banks controlled by politicians were likely to issue lower-quality credit (and perhaps fund this credit using MBS). We tested for this in two ways. First, we use to the proportion of local government board members (which is limited by local statues), relying on data from Fonseca Diaz (2005). Second, we cross-referenced board members' names with those of all national elected deputies (members of the lower house of congress), and counted the number of former deputies among board members. We also control for bank size (total assets) and geographical concentration. The latter is calculated as the percentage of bank branches located in the bank's home province.[12] Finally, in a separate analysis we analyze data on non-performing loans and non-performing loan coverage ratios[13].

In order to account for the geographic economic heterogeneity of Spain, we control for province population, which is highly correlated with provincial GDP (but available at earlier time points);

our this measure aggregates province-level data to banks by weighting province population by the proportion of each banks' branches located in each province. In supplementary analyses (see appendix), we also tested whether per capita GDP, the share of construction in provincial GDP, housing construction licenses per capita, and the value of real estate transactions influences MBS issuance. These variables are all defined in terms of the bank's primary province. Our models also include use three broad regional dummies to control for geographical variation not measured elsewhere (central Spain is the comparison group). As we will see below, introducing province-level variables introduces a substantial complication into our analysis.

We initially hoped to leverage the time series properties of our date by estimating panel models incorporating autocorrelation terms following methods proposed by Hays et al. (2010). However, non-stationarity and serial correlation are serious problems in this analysis, and common solutions are not appropriate given key features of our data.[14] Given this, we decided to focus on purely cross-sectional models, sacrificing statistical degrees of freedom but avoiding bias due to time-series issues. Thus, we estimate models of the total cumulative issuance of MBS in 2006, the peak year of the expansion of the housing market.[15] Because the MBS market emerged de novo, this is equivalent to the increase in issuance from inception. Although this precludes a direct examination of dynamics, in our view this approach is fundamentally more conservative because it avoids drawing inferences based on results contaminated by time series issues. This also enables us to avoid endogeneity in our network weights by substantially lagging these measurements. In our primary specification of competitive relations, we use the competitive relations between banks in 1995, at the beginning of the mortgage boom. We also measure bank and province-level variables in the mid–1990s. Collaborative relations cannot be measured with this substantial lag, because by definition joint issuance only occurs after the inception of the market. Hence, this measure is contemporaneous.

4 Results

We begin by asking whether MBS issuance played a significant role in the savings bank crisis by analyzing the association between issuance levels at the peak of the boom and measures of bank distress during the crisis. We analyze two measures of bank distress: non-performing loans (NPL) and NPL coverage. The former are loans in default or close to it (e.g. loans in which borrowers have not made payments for 90 days), whereas the latter captures the extent to which a bank can absorb losses from these loans. Thus, both measures capture aspects of bank vulnerability in the credit crisis. We regard NPL coverage as the better indicator because it incorporates both information about failed loans and the ability of the bank to absorb them, but we were able to find these data for fewer cases.[16] We capture both variables in 2009, when the NPL levels had already increased substantially but before bank interventions due to insolvency mean that the worst-performing banks begin to drop out of the data.[17] Descriptively, NPL levels generally accord with qualitative expectations about which of the larger and more visible banks had the worst performance, but also shed light on poor performance among smaller and less widely noticed banks. For example, two of the earliest banks to fail (Caja Castilla la Mancha and Cajasur) have the highest level of NPL in the data. At the same time, several small Catalonian banks that attracted less public attention also appear at the top of the NPL distribution.

Because there are two outliers with extreme levels of NPL relative to both NPL coverage and MBS issuance, we estimate robust regression in the case of NPL and OLS in the case of NPL coverage. Both analyses reported in table 1 imply that MBS issuance strongly predicts bank distress, even when controlling for credit growth. Banks with comparatively low levels of MBS issuance (equal to around half of bank capital) had, on average, non-performing loans around the first quartile of the overall NPL distribution (excluding outliers). In contrast, banks issuing MBS equal to twice their capital tended to have above-average NPL levels. The association with NPL coverage is even stronger. Low -level issuers could on average cover 87% of their non-performing loans, while those issuing MBS amounting to twice their capital could cover only 74% of non-performing loans. The six highest issuers, with MBS issuance amounting to four times bank capital or more, could cover 60% or fewer of non-performing loans.

We also test whether credit to real estate developers mediates this relationship because of the emphasis on this factor in the literature, as dicussed above. Consistent with this, banks with a higher percentage of loans to developers in their portfolios had higher levels of NPL at the outset of

Table 1: RMBS issuance and nonperforming loans (NPL)/NPL coverage

DV Model	NPL Robust	NPL Robust	NPL Robust	NPL Robust	Cover OLS	Cover OLS	Cover OLS	Cover OLS
Cumulative RMBS	0.34***		0.30***	0.33***	−0.09***		−0.08**	−0.08**
	(0.08)		(0.08)	(0.06)	(0.02)		(0.02)	(0.02)
Δ credit		0.20*	0.09			−0.04†	−0.01	
		(0.09)	(0.11)			(0.02)	(0.02)	
Credit to developers				0.03*				−0.00
				(0.01)				(0.00)
Num. obs.	44	44	44	41	41	41	41	40
R^2	0.19	0.07	0.21	0.34	0.27	0.08	0.28	0.26
Adj. R^2	0.17	0.05	0.17	0.30	0.25	0.05	0.24	0.22
RMSE	-	-	-	-	0.22	0.25	0.23	0.23

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

the crisis. However, this association does not substantially mediate the effect of MBS issuance on NPL, and loans to developers have no apparent impact on coverage. Thus, this analysis strongly supports the view that mortgage securitization played a central role in the Spanish savings bank crisis.

4.1 Baseline model

In order to test for relational herding in the Spanish MBS market, we first seek to establish a baseline model of MBS issuance capturing the influence of bank and province-level variables. In order to test for managerial experience, we use executive turnover. First, consistent with Cuñat and Garicano (2009), we find that executive turnover is associated with higher MBS issuance, particularly after controlling for regional variation. Second, the models in table 2 include a measure of political control of bank boards, the percentage of board members appointed by local governments. Also consistent with Cuñat and Garicano (2009), we do not find evidence to support politicized lending: in model 1, the coefficient for this variable has an unexpected significant negative sign, but this effect is not robust to the inclusion of region dummies. In other results (see appendix table TBD) we test an additional indicator of bank politicization, namely whether the bank's executive had served in the lower chamber of congress; this variable provides no evidence in support of this view. To be clear, we are not arguing that there was no politicization of Spanish savings banks, only that we cannot find evidence that politicization explains variation across banks in the intensity of securitization. It may be that more informal measures of politicization would yield more interpretable results.[18] Politicization is often thought to apply primarily to loans to real estate developers; as we have shown above, these loans are associated with bank distress independent of the consumer-focused mortgage market.[19] Thus, politicization may well explain other aspects of the crisis, though Cuñat and Garicano (2009) find no association between politicization and credit at the bank level.

In addition to testing these alternative hypotheses, our models include several bank-level control variables. First, we control for total bank assets (measured before substantial growth in MBS began) to account for the wide variation in bank size. Despite the fact that our MBS issuance measure includes bank capital (itself highly correlated with assets) in the denominator, we find a negative and significant correlation between assets and MBS issuance. We interpret this effect as suggesting that, given the skewed distribution of bank size, it was 'easier' for small and medium-sized banks to issue MBS amounting to a significant multiple of bank capital than for larger banks. This is consistent with the fact that the two largest banks with national scope had relatively low levels of MBS issuance relative to their capital. We also control for the change in assets (between 1995 and 2005) and find that banks that grew in size tended to issue more MBS, though this effect disappears once regional dummies are included. Our models also include a measure of provincial bank concentration (the proportion of branches located in the primary province, generally the location of the bank's headquarters). We include this measure because of the possibility that our competitive weights used below reflects the heterogeneity or concentration of bank networks. We find no evidence to support this.

Our baseline model also includes the timing of market entrance — that is, the time elapsed between the first issuance of MBS by a Spanish savings bank (1993) and each bank's first issuance. Thus, the positive and significant coefficient indicates that early market entrants also tended to issue greater volumes by the peak of the boom. We include this term because, as noted above, our modeling strategy differs from many studies of social influence and diffusion. Rather than model the *timing* of adoption (as with, for example, event history approaches) we are more interested in the

	Model 1	Model 2	Model 3	Model 4
Constant	1.20	-0.32	-0.47	0.12
	(1.18)	(0.96)	(0.87)	(0.88)
Total assets (1995)	-0.26^{**}	-0.21^{**}	-0.17^{*}	-0.14^{*}
	(0.09)	(0.07)	(0.07)	(0.07)
Δ assets	0.07^{*}	0.04	0.03	0.03
	(0.03)	(0.02)	(0.02)	(0.02)
Main prov. concentration	2.09	1.06	0.26	0.42
	(1.04)	(0.84)	(0.80)	(0.78)
Δ main prov. concentration	1.76	0.92	-0.25	-0.89
	(2.00)	(1.68)	(1.56)	(1.56)
Political control	-0.04^{**}	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Leadership turnover	0.20	0.22^{*}	0.18^{*}	0.17^{*}
	(0.11)	(0.08)	(0.08)	(0.07)
Market entrance	0.16^{*}	0.22^{**}	0.18^{**}	0.20^{**}
	(0.08)	(0.06)	(0.06)	(0.06)
Region: Mediterranean		1.11^{*}	1.26^{**}	1.06^{*}
		(0.44)	(0.40)	(0.40)
Region: Catalonia		2.49^{***}	0.85	0.69
		(0.48)	(0.69)	(0.68)
Region: North		0.57	0.39	0.37
		(0.49)	(0.45)	(0.43)
Province population (weighted)			0.69^{**}	6.25^{**}
			(0.23)	(1.97)
Province population^2 (weighted)				2.00
				(1.13)
R^2	0.42	0.68	0.75	0.77
Adj. R^2	0.31	0.58	0.66	0.68
Num. obs.	46	46	46	46
RMSE	1.28	0.99	0.89	0.87

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2: Baseline OLS models

intensity of adoption, given the clear evidence of heterogeneity in participation in the market. One hypothesis is that social influence processes drove both the timing and intensity of MBS adoption. However, in a series of hazard models reported in the appendix, we do not find any evidence of social influence effects on the timing of adoption. As we also showed above, however, adoption of the varieties of MBS that drove issuance volume during the boom years (multi-issuer cedulas and 'non-conforming' transfer certificate-based funds) occurred extremely quickly (within three years) of their introduction. We doubt whether the particular timing of market entrance during these short time periods is more consequential to the overall boom dynamics than the intensity of issuance. Thus, we control for timing of diffusion, rather than seeking to model it.

In addition to these bank-level variables, we also capture variation occurring at the province level. Our baseline model shows that banks with branches in more populous provinces also issue greater volumes of MBS. As mentioned above, provincial population is highly correlated with provincial GDP (particularly in the cross-section) and we interpret this as an effect of provincial economic wealth, broadly understood. In other words, banks with more branches in populous, economically important provinces issued more MBS. We chose a quadratic specification of this wealth effect; while the second-order term is not statistically significant in all models, this specification improves goodness-of-fit and is statistically significant in many of our social influence models below. Because this wealth effect also influences interpretation of our models, as shown below, inclusion of the best-fitting version of this variable is the most conservative approach. The quadratic specification implies that there is little difference in MBS between small and medium-sized provinces, but banks headquartered in the wealthiest and most populous provinces tended to issue larger volumes of MBS.

Finally, region dummies show that, as expected, banks headquartered along the Mediterranean coastline and in Catalonia issued larger volumes of MBS relative to those in central Spain. However, the Catalonia dummy falls substantially in size and loses significance after incorporating the wealth effect just discussed. Thus, while the Mediterranean litoral (excluding Catalonia) is overrepresented among MBS issuers, the concentration of MBS issuance among banks with Catalonian branches appears consistent with the region's comparative wealth.

Appendix table TBD includes additional variables capturing the provincial heterogeneity of the Spanish housing boom: the share of construction in provincial GDP, the (log) number of construction permits , and the value of real estate transactions. All of these variables are defined either with respect to the main province of each savings bank or as a weighted average of provinces as with the weighted provincial population measure described above. Because we see all of these variables as potentially endogenous to the MBS-driven credit boom, our interest here is controlling for these variables *before* the boom. Thus, we use the earliest available data for each of these variables. None is significantly associated with MBS issuance.

4.2 Social influence models

We begin our analysis of social influence proper by presenting zero-order models that include only autocorrelation terms (and constants) without any bank- or province-level variables in table 3. As the table shows, these models suggest the presence of autocorrelation in competitive networks, lending initial support to the relational herding hypothesis. Results for collaborative and communicative ties do not suggest influence processes operating through these channels. Similarly, we find no initial evidence of a geographic diffusion process in MBS issuance. This latter finding is relevant to the frequent use of geographical proximity as a proxy for social networks: we find that geography is loosely correlated with more sociologically informed network measures and does not appear to capture the same process.

Table 4 adds variables included in our baseline model to the autocorrelation models. For reasons explored momentarily, all of these models include a geographical autocorrelation term, which is negative and statistically significant in most models. These results confirm the zero-order finding reported above: as model 3 shows, there is a substantial and statistically significant competitive autocorrelation coefficient, consistent with a social influence process traveling through the network of competitive inter-bank relations. In contrast to the zero-order results, model 4 in table 4 implies negative autocorrelation in the collaborative inter-bank network. However, further investigation shows that this finding is highly sensitive to the specification of the relational matrix; using specifications that account for relative size, we find a positive and significant coefficient.

	Model 1	Model 2	Model 3	Model 4
Constant	1.31	1.47*	1.04*	2.06*
	(0.92)	(0.59)	(0.48)	(1.03)
Geographical autocor.	0.06			
	(0.05)			
Communicative (political) autocor.		0.35		
		(0.24)		
Competitive autocor.			0.72***	
			(0.12)	
Collaborative autocor.				0.08
				(0.45)
Log Likelihood	-84.44	-83.70	-81.10	-84.66
Num. obs.	46.00	46.00	46.00	46.00
AIC	172.88	171.40	166.20	173.33

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3: Baseline autocorrelation models

However, it is impossible to exclude the possibility that this coefficient exclusively reflects relative size. Therefore, we refrain from giving a substantive interpretation to this highly sensitive result.

A key issue in our main finding of positive autocorrelation in the competitive network is the dependency between this finding and the unexpected negative geographical autocorrelation term. The competitive autocorrelation finding depends on inclusion of the geographical autocorrelation term: without this, competitive autocorrelation falls in magnitude and loses statistical significance. Because of this, we devote the methodological appendix to a full discussion of this issue; in brief, this occurs because a modest positive correlation between geographical and competitive weights, and the negative geographical autocorrelation which emerges after controlling for province-level variables. Here, we focus on the substantive import of this unexpected negative geographical autocorrelation.

The classic example of negative spatial autocorrelation is a ‘checkerboard’ pattern (with dark and light squares corresponding to high and low values). Exploratory analysis showed that this negative autocorrelation emerges due to inclusion of province-level variables (in particular, province population) and/or region dummies in the baseline model. Net of these variable, the within-province variation is greater than the unconditional variance. This pattern is visualized in figure 4, which shows each bank and its position on the map of Spain, with points scaled to the (squared) residuals from the baseline model in table 2. The clearest illustration of the pattern is the region of Catalonia (in north-eastern Spain). Fully ten banks had their headquarters in Catalonia, larger by far than any other region. Catalonia is a populous and wealthy region, and many of its banks issued large volumes of MBS. At the same time, as figure 4 shows, the variation within Catalonia net of this effect is substantial. However, this pattern in not limited to Catalonia, and can be seen in other provincial banking hubs. Thus, the negative geographical autocorrelation in figure 4 reflects the high variance among banks in proximate locations, such as Catalonia.

Our conclusion from this discussion and from the appendix is that, once we have disentangled the effects of physical distance and province-level factors, there is robust support for the competitive autocorrelation effect. Neither collaborative nor partisan autocorrelation has such an association. In the appendix, we show that this effect also holds when this model is estimated by OLS.

Figure 5 displays this result graphically. For purposes of visual clarity, the figure separates 'high' and 'low' MBS issuers in panel a and b, respectively. Nodes (banks) are scaled to the volume of MBS issuance and darker-shaded ties represent stronger competitive relations. The bottom cluster of banks in panel a includes a number of small to medium Catalonian banks. Notably, however, this cluster is not strictly Catalonian; it also includes the Andalusian Caja Granada and Guadajara-based Ibercaja. By the same token, two more modest Catalonian issuers in panel b do not figure in this cluster. This illustrates the loose overlap between geographical proximity and competitive networks. The upper cluster of panel a also features some of the most notorious poor performers during the crisis and illustrates that these banks competed with one another, sometimes across large geographical distances. For example, the high-issuing Caja Cantabria (headquarted along the Bay of Biscay in the North) competed closely with Caja del Mediterraneo (CAM) on the Mediterranean litoral. Thus, intensive issuers of MBS were embedded in this competitive network, while those peripheral to the network tended to limit their MBS issuance. This is the basic pattern captured by our statistical models.

Figure 4: Negative geographical autocorrelation net of province-level factors

	Model 1	Model 2	Model 3	Model 4
Constant	3.89	4.14	6.94***	5.47*
	(2.08)	(2.28)	(2.01)	(2.63)
Total assets (1995)	−0.13*	−0.13*	−0.11*	−0.17*
	(0.05)	(0.05)	(0.05)	(0.07)
Δ assets	0.03	0.03	0.02	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Main prov. concentration	0.70	0.61	0.35	0.61
	(0.61)	(0.61)	(0.57)	(0.60)
Province population	6.13***	6.15***	6.56***	6.26***
	(1.53)	(1.52)	(1.40)	(1.51)
Province population^2	1.79*	1.63	1.68*	1.78*
	(0.88)	(0.91)	(0.81)	(0.86)
Region: Mediterranean	0.88**	0.91**	0.69*	0.80*
	(0.33)	(0.33)	(0.31)	(0.34)
Region: Catalonia	1.15*	1.47*	0.45	0.99
	(0.56)	(0.71)	(0.52)	(0.57)
Region: North	0.33	0.24	0.48	0.32
	(0.33)	(0.33)	(0.32)	(0.33)
Market entrance	0.21***	0.18***	0.20***	0.20***
	(0.05)	(0.05)	(0.04)	(0.05)
Leadership turnover	0.17**	0.15*	0.17**	0.15**
	(0.06)	(0.06)	(0.05)	(0.06)
Political control	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Geographical autocor.	−0.24*	−0.21	−0.47**	−0.23*
	(0.12)	(0.12)	(0.14)	(0.10)
Communicative (political) autocor.		−0.27		
		(0.32)		
Competitive autocor.			0.85***	
			(0.01)	
Collaborative autocor.				−0.62*
				(0.30)
Log Likelihood	-49.48	-49.24	-46.08	-48.89
Num. obs.	46.00	46.00	46.00	46.00
AIC	124.96	124.48	118.16	123.79

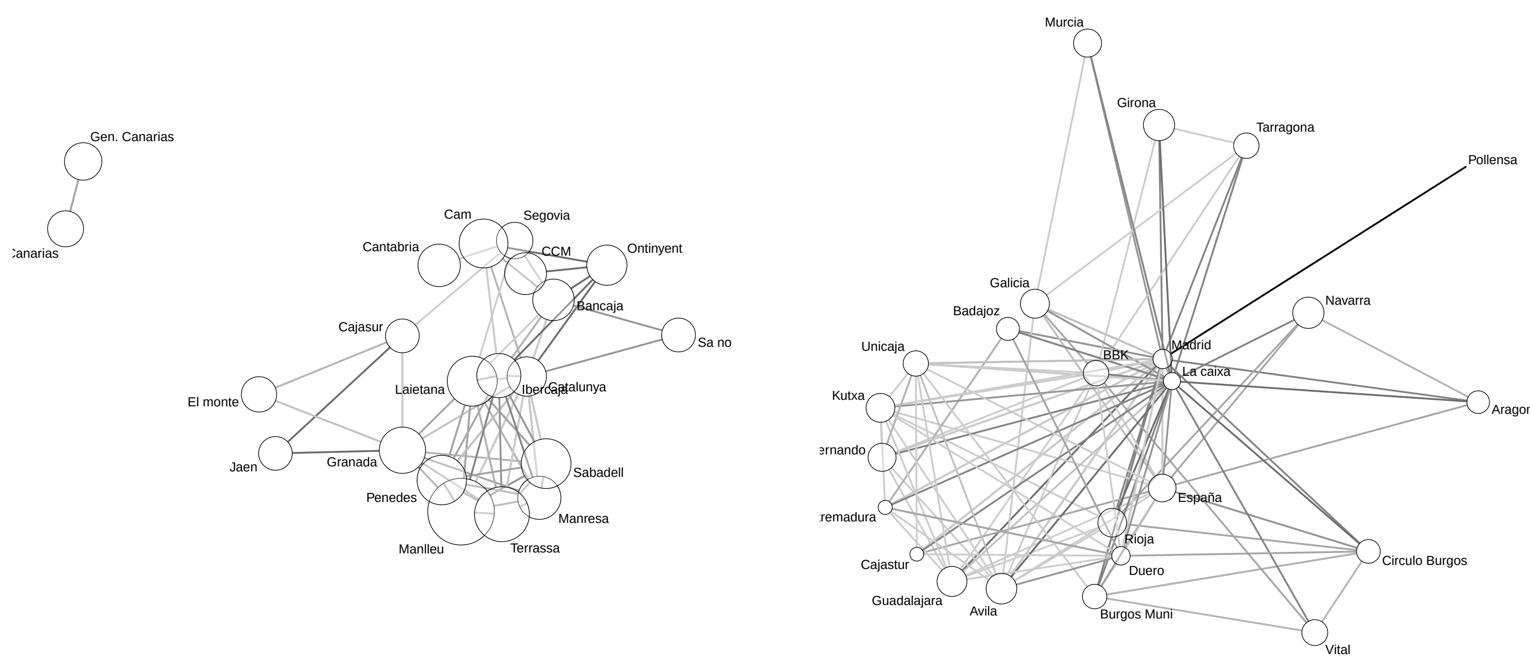
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 4: Autocorrelation models of RMBS issuance

Figure 5: Competetive branch network, by issuance levels

(a) RMBS issuance ≥ 2

(b) RMBS issuance < 2



We argue that the assumptions required to interpret these findings as capturing a social influence process rather than network homophily are relatively weak. Shalizi and Thomas (2011) argue that homophily and influence are generally confounded due to the presence of unobservable latent traits that affect both network formation and the outcome of interest. A homophily-based explanation for our findings would suggest that banks with some underlying unobserved attribute (e.g. bank managers' growth ambition) tend to select into high-growth provinces, and thus into competitive relations with similar banks. If banks with this underlying growth ambition are those that issue the largest volumes of MBS, we would observe the competitive autocorrelation effect.

While we cannot definitely rule out such a homophily effect, we find this interpretation less plausible than social influence for three reasons. First, our competitive network measure substantively pre-dates the emergence of the process that generated the outcome, that is, the MBS market itself. Thus, any unobservable confounder must be a factor capable of affecting both MBS issuance and competitive network formation *at a time when MBS issuance as such did not exist.* Stated differently, only factors which had a rapid effect on competitive networks but long-lasting effect on bank behavior in the future could make homophily look like influence in these data.

Second, the homophily posited by this hypothesis is indirect; on this model, banks select into mortgage-boom provinces and homopholous ties result only if banks happen to chose the same provinces — but selection of provinces for branch expansion is also constrained by other factors (e.g. proximity to home province). In addition, we expect any such process to be relatively slow due to the inherent stickiness of branch networks. Because of these factors, we expect any homophily effect to be relatively weak in this context.

Finally, we are able to address this issue empirically by leveraging temporal variation in competitive networks. During the mortgage boom, banks expanded their geographical scope, often selecting into high-growth provinces. This expansion induced greater competition as banks faced new competitors in their home provinces, or entered provinces already occupied by established incumbents. If these selection processes reflect underlying bank traits also correlated with MBS issuance, then we expect to see an increase in competitive autocorrelation in more recent network measures. To address this possibility, we re-estimate model 3 in table 4 using a competitive weights network based on branch locations in each year between 1995 and 2006. We find no evidence of an increasing autocorrelation trend and indeed, in the 2006 network the autocorrelation parameter declines to .34 and loses statistical significance (SE=.33). Thus, the evolution of the competitive branch network between 1995 and the peak of the boom — reflecting any selection which may have occurred on attributes correlated with RMBS issuance — reduces autocorrelation rather than increasing it, mitigating concerns about homophily confounding influence.. As discussed above, the Spanish MBS market displays additional variation that provides empirical leverage for our analysis: the different underlying assets pooled in the securitization funds. Recall that the earliest, most conservative form of securitization introduced in the mid–1990s (mortgage share securitization) was eclipsed by two new forms: covered bond and transfer certificate securitizations. These novel and risky financial innovations accounted for the bulk of market growth during the peak years of the boom beginning around 2000. In order to leverage this variation, we re-estimate model 7 in table 4 for MBS issuance disaggregated by the category of underlying assets. Table 5 shows that the competitive autocorrelation effect already identified is concentrated in the more novel and risky segments of the market (covered bond and transfer certificate securitization); there is no evidence of a social influence process in the earlier mortgage share securitization market. In other words, our results show that the competitive diffusion process occurred precisely in the rapidly-growing segment of the market that drove the boom (and crisis). These models also indicate that the negative geographical autocorrelation term is concentrated in these segments of the market.

It is useful to consider this result in light of the disaggregated diffusion process illustrated in figure 3 above. Both novel technologies diffused to nearly the entire target population within three years of introduction. The earliest forms of mortgage securitization show no sign of a social influence process. In contrast, the rapidly diffusing (and riskier) forms of securitization, which account for the bulk of the rapid growth in issuance after 2000, show strong signs of a competitively-driven diffusion process. We interpret the concentration of the competitive social influence process in the newest, fastest-growing segment of the market as supporting the endogenous model of financial cycles that motivates our analysis. Under this model, we expect social influence effects to be observable in precisely these market segments. We thus summarize the Spanish financial crisis in

	Participation	CB	Transfer
Constant	0.15	4.98**	4.30*
	(0.34)	(1.87)	(2.19)
Total assets (1995)	0.00	0.01	−0.14*
	(0.01)	(0.04)	(0.07)
Δ assets	−0.00	−0.02	0.04*
	(0.00)	(0.01)	(0.02)
Main prov. concentration	−0.12	−0.43	0.92
	(0.14)	(0.34)	(0.50)
Province population	0.35	3.85***	2.18
	(0.34)	(0.83)	(1.22)
Province population^2	−0.39*	0.47	1.43*
	(0.19)	(0.49)	(0.71)
Region: Mediterranean	0.20*	0.24	0.21
	(0.08)	(0.19)	(0.28)
Region: Catalonia	0.46**	−0.09	0.81
	(0.14)	(0.34)	(0.53)
Region: North	0.06	−0.15	0.40
	(0.07)	(0.19)	(0.27)
Market entrance	0.02*	0.08**	0.08*
	(0.01)	(0.03)	(0.04)
Leadership turnover	−0.01	−0.02	0.17***
	(0.01)	(0.03)	(0.05)
Political control	0.00	−0.00	−0.01
	(0.00)	(0.00)	(0.01)
HQ spatial autocorrelation	−0.03	−0.40**	−0.69**
	(0.12)	(0.15)	(0.24)
Communicative autocorrelation	−0.39	−0.21	−0.34
	(0.40)	(0.34)	(0.37)
Competitive autocorrelation	−0.33	0.58***	0.76***
	(0.28)	(0.04)	(0.03)
Collaborative autocorrelation	−0.58	−0.75*	0.04
	(0.68)	(0.30)	(0.22)
Log Likelihood	20.24	-22.39	-41.32
Num. obs.	46.00	46.00	46.00
AIC	-14.48	70.78	108.64

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 5: Disaggregated autocorrelation models

the following way. The policy and institutional infrastructure necessary for securitizing mortgages issued by Spanish savings banks existed from the mid 1990s. However, while nearly half of Spanish savings banks had participated in this market by 2000, issuance volumes remained low. Two new securitization technologies introduced after 2000 changed this panorama; these enabled banks to securitize large volumes of mortgage debt (during the years of peak growth in housing prices) by pooling extensively across banks and including 'non-conforming' mortgages. Banks situated in a cluster of competitive ties (which pre-dated the securitization market itself) were the largest participants in these new markets. They issued the largest volumes of MBS, and ultimately accumulated to largest share of non-performing loans. To summarize, this analysis provides strong evidence that a competitive influence process played a central role in the growth of the MBS market in Spain, ultimately resulting in a widespread crisis in the savings bank sector. This social influence process was concentrated in the novel and risky segments of the market that drove the bulk of MBS issuance during the peak years of the boom. Our findings are contingent on proper specification of regional variation and spatial dependencies in models that control for influential province-level variables and variation across broad regions of Spain. But we find that once these spatial patterns are appropriately modeled, the evidence of a competitive diffusion process is robust.

5 Conclusion

As argued in the introduction, theories of the social dynamics of financial markets have become commonplace in economics, but largely ignore sociological models of social influence and diffusion processes. In this paper, we use the latter approach to show that a competitive influence process was a key dynamic in the mortgage securitization boom in Spain. This finding is in keeping with previous sociological research on diffusion processes, which often find competitive dynamics. However, as far as we are aware, no papers have previous tested these models in a financial herding context. Furthermore, we test four distinct channels of social influence (including three theoretically specified channels and one methodologically-driven geographical specification), finding that competitive relations were the primary channel of social influence in this context. Our results show that social influence and diffusion studies should be cautious in assuming that geography is a good proxy for social networks, and also be attentive to the differences between distinct network content.

We urge scholars interested in the social dynamics of financial markets to expand beyond a focus on temporal clustering in investment decisions, in order to examine 'spatial' (including socio-spatial) heterogeneity in diffusion. A key advantage of these models is that it enables us to use cross-unit variation (whether units are individuals or firms) to examine social dynamics. Even when many investors, banks or other financial actors rush into a particular investment or asset class, others remain aloof. Susceptibility to herding is variable. If this is the case, then researchers have ignored one important avenue for testing for 'herding' or, more generally, social influence in financial markets.

Our results have an important policy implication. Since their near-death experience in the wake of the 2008 financial crisis, securitization markets have seen a surprising renaissance. In Europe, the European Central Bank played a key role in the post-crisis securitization market (Braun, 2018). The ECB's post-crisis embrace of securitization is predicated on the notion that the problems plaguing pre-crisis securitization markets could be effectively contained. This in turn rests on the assumption that incentive problems associated with the 'originate to distribute' securitization model prevalent in the US were a primary source of instability. Our results cast doubt on this assumption by showing that in Spain — the largest participant in the Eurozone securitization markets relative to banking sector size — mortgage securitization is strongly related to bank distress despite the absence of an originate to distribute model. Furthermore, we provide an account of the Spanish banking crisis that is not dependent on any particular institutional feature of the mortgage securitization system, but rather the endegenous tendency of financial markets to produce boom-bust cycles. By presenting evidence supporting a social influence channel in generating a financial boom, we emphasize that the risks of mortgage securitization run deeper than any particular institutional feature.

6 Methodological appendix

We find that omitting the geographical autocorrelation term included in our preferred specification while simultaneously controlling for province-level variables and regional dummies results in a substantial decrease in the size of the competitive autocorrelation coefficient and loss of statistical significance. In this appendix, we explore the reasons for this and explain why we believe that proper specification requires inclusion of a geographical autocorrelation term.

First, we note that after controlling for the bank and province-level variables included in our baseline model (and excluding other autocorrelation terms), the geographical autocorrelation parameter becomes negative and statistically significant (see model 1 in table 4). This is a reversal in sign from the zero-order model reported in table 3. We found that this change in coefficients reflects the inherent dependency between province-level variables, regional dummies, and geographical autocorrelation. We define a home province as the province in which the bank has the largest number of branches. Typically, this is also the province where the bank's headquarters is located. Given this, two banks whose branches are mostly located within their home province will have similar values for the population variable.[20] Given that the home province is also typically the location of the bank's headquarters, these banks are also close in the geographical weights matrix. Finally, such banks are also by definition located in the same broad regions. This particularly affects the seven banks located in Catalonia: these banks have similar values for population, are physically close, and also score one on the 'Catalonia' dummy. This dependency would arise with *any* variable measured at the province level and aggregated to the bank level.

Negative autocorrelation occurs when units with high and low values tend to be proximate (rather than high values clustering with other high values and low values with low values). The classic example is a 'checkerboard' pattern. In our case, bank headquarters can be not only proximate but literally in the same location, to the extent that they are headquartered in the same province.[21] Thus, negative autocorrelation will occur if within-province (and neighboring province) variation is high. Appendix table XXX shows that while there is mild negative geographical autocorrelation in a simple model with only province population and regional dummies, there is very strong negative autocorrelation of the *residuals* from a model including only province population and regional dummies. In other words, variation in MBS not accounted for by the province and region-level variables in our baseline model is negatively autocorrelated, reflecting the high variance of MBS issuance within provinces and between neighboring provinces.

In addition, the competitive weights matrix is positively correlated with the geographical weights matrix (r= .25). Although this correlation is not large, implying that these matrices do capture distinct information, it does imply that estimation of the competitive autocorrelation effect *without* netting out the negative geographical autocorrelation effect will result in an under-estimate of the former. That is, estimate will reflect both positive competitive autocorrelation and negative geographical autocorrelation (net of province and region-level factors). Thus, we conclude that the the best modeling strategy for testing our substantive social influence processes is to include the geographical autocorrelation term in our models.

Notes

[1]Informational models are based on the intuition that (for example) customers rationally might use the queues outside restaurants as a signal, given uncertainty about underlying quality. In reputational models, managers or investors herd because the potential reputational costs of failure are lower if they chose behavior similar to that of peers.

[2]Scholars in the social studies of finance tradition might reject the characterization of such behavior as asocial, noting that price records are the material embodiment of social practices. Without disputing this point, we underscore the critical distinction between social influence models in which actors emulate particular others and in which they emulate an aggregate index of others' behavior.

[3]One exception is Kaustia and Knüpfer (2012); this paper uses geographical proximity, on which our comments below are relevant.

[4]OECD data.

[5]In order to estimate these models with multiple autcorrelation terms, we use maximum likehilhood-based estimation code written by Slez (2016) based on the methods in Hays et al. (2010)

[6]A more ideal measure would be the bank's exposure to MBS: that is, the cuulative issuance less any repayment of the fund's principal. Unfortunately, there is no easy way to calculate repayment of each fund. We do not think this is a problem because Spanish MBS were long-term funds (e.g. 50 years) and the time transpired between the years of most growth and the peak of the market is short (around 5 years). In addition, many Spanish MBS made only annual coupon (interest rate) payments and paid down the fund's capital only on closure, so there was no actual depreciation of the fund's capital.

[7]Thanks to Sebastian Lavezzolo for providing these data.

[8]We looked for evidence of a board-based interlocking directorate by cross-referencing the names of bank board members across all banks in test year. We did not find any individuals who sat on the board of more than one savings bank.

[9]In the Spanish context, the 52 "provinces" are small geographical units (generally with only one major city) while the 17 "comunidades autas" are larger political units that are the equivalent of U.S. states or German Lander.

[10]Because we emphasize the distinction between geographical proximity and competitive ties, it is worth clarifying the role of geography in this measure. In contrast to geographic proximity measures, this measure does not emphasize the distance between locations but the extent overlap in multi-location enttities. It remains in some sense a socio-spatial measure, but not one based on sheer proximity.

[11]X Cuñat and Garicano (2009) coded the career backgrounds of bank managers for prior financial experience and economics education. We were unable to obtain these data and are skeptical about the objectivity of coding financial experience (given that, by definition, all bank managers have some financial experience). Our use of executive turnover is motivated by the fact that Cuñat and Garicano (2009) found this to be correlated with their human capital measures.

[12]This measure performs somewhat better than the Herfindahl index of concentration across all provinces.

[13]These data are not readily available. We found NPL and coverage data for roughly 40 banks on the web page of one of the firms managing securitized funds and added additional observations from banks' annual reports.

[14]A common methodological approach given these issues would be to focus on data expressed in terms of first differences. We think this approach is inappropriate here for several reasons. First, MBS issuance is 'lumpy' in time: many smaller banks issue no MBS in given year, perhaps because (given their small size) their funding needs could be met by issuance at a less-than-yearly frequency. Second, first-diferenced estimation entails the additional assumption that (in this context) banks observe the interanual change in issuance (or change with a lag) of other banks, which is a stronger assumption than that banks are generally aware of peers' total issuance volume.

[15]Housing prices peaked in 2006, although MBS issuance peaked in 2008. In addition, a merger of two banks in 2007 means that the number of units available falls in this year.

[16]We have NPL data for 44 cases because of the 2007 merger which eliminated two banks. Coverage data are missing for three additional banks.

[17]Beginning in 2010, banks begin to disappear from the available data, and this missing data is clearly correlated with bank distress, as the worst performing banks failed first.

[18]However, Cunat find…

[19]However, we also find a negative correlation between representation of politicians on bank boards and loans to developers.

[20]Our branch-weighted population measure is highly correlated with an alternative specification which assigns a value based on the population of their home province. In the latter case, banks with the same home province have exactly the same value on the provincial population variable.

[21]Our geographical weights matrix treats the proximity of banks headquartered in the same city as equal to 1, because we do not take into account within-city distances.

References

Abrahamson, E. and L. Rosenkopf. 1993. "Institutional and Competitive Bandwagons." *Academy of Management Review* 18:487–517.

Acharya, Viral V., Philipp Schnabl, and Gustavo Suarez. 2013. "Securitization without risk transfer." *Journal of Financial Economics* 107:515–536.

Adler, Patricia A. and Peter Adler. 1984. *The Social dynamics of financial markets*. JAI Press.

Akerlof, George A and Robert J Shiller. 2009. *Animal Spirits: How Human Psychology Drives the Economy, and Why it Matters for Global Capitalism*. Princeton: Princeton University Press.

Alberdi, Baralides. 1997. "Recent Mortgage Market Development in Spain." *Housing Finance International* pp. 23–30.

Anselin, Luc. 2002. "Under the hood issues in the specification and interpretation of spatial regression models." *Agricultural Economics* 27:247–267.

Arranz Pumar, Gregorio. 2009. "El mercado hipotecario español: Los títulos del mercado hipotecario." *Colegio Universitario de Estudios Financieros Working Paper* .

Banerjee, Abhijit V. 1992. "A Simple Model of Herd Behavior." *The Quarterly Journal of Economics* 107:797–817.

Bikhchandani, Sushil and Sunil Sharma. 2001. "Herd Behavior in Financial Markets: A Review." *IMF Staff Papers* 47:279–310.

Bothner, Matthew S. 2003. "Competition and Social Influence: The Diffusion of the Sixth-Generation Processor in the Global Computer Industry." *American Journal of Sociology* 108:1175–1210.

Braun, Benjamin. 2018. "Central banking and the infrastructural power of finance: the case of ECB support for repo and securitization markets." *Socio-Economic Review* .

Brown, Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott Weisbenner. 2008. "Neighbors Matter: Causal Community Effects and Stock Market Participation." *Journal of Finance* 63:1509–1531.

Brunnermeier, Markus Konrad. 2001. *Asset pricing under asymmetric information : bubbles, crashes, technical analysis, and herding*. Oxford University Press.

Burt, Ronald. 1987. "Social Contagion and Innovation: Cohesion Versus Structural Equivalence." *American Journal of Sociology* 92:1287–1335.

Carbó-Valverde, Santiago, David Marques-Ibanez, and Francisco Rodríguez-Fernández. 2012. "Securitization, risk-transferring and financial instability: The case of Spain." *Journal of International Money and Finance* 31:80–101.

Catarineu, Eva and Daniel Pérez. 2008. "La titulización de activos por parte de las entidades de crédito: El modelo español en el contexto internacional y su tratamiento desde el punto de vista de la regulación prudencial." *Estabilidad Financiera* 14:89–121.

Centola, Damon. 2018. *How Behavior Spreads : the Science of Complex Contagions*. Princeton: Princeton University Press.

Centola, Damon and Michael Macy. 2007. "Complex Contagions and the Weakness of Long Ties." *American Journal of Sociology* 113:702–734.

Cipriani, Marco and Antonio Guarino. 2014. "Estimating a structural model of herd behavior in financial markets." *American Economic Review* .

Cuñat, Vicente and Luis Garicano. 2009. "Did Good Cajas Extend Bad Loans? Governance, Human Capital and Loan Portfolios." In *Fedea annual policy conference, Madrid, Spain*.

Davis, Gerald F. 1991. "Agents without Principles? The Spread of the Poison Pill through the Intercorporate Network." *Administrative Science Quarterly* 36:583–613.

Davis, Gerald F and Henrich R Greve. 1997. "Corporate Elite Networks and Governance Changes in the 1980s." *American Journal of Sociology* 103:1–37.

de Barroon Arniches, Inigo. 2012. *El hundimiento de la banca: cronica de coomo gestores, supervisores y politicos provocaron la mayor crisis en la historia del sistema financiero espanol [FIX ACCENTS]*. Madrid: Los libros de la catarata.

DiMaggio, Paul and Filiz Garip. 2012. "Network Effects and Social Inequality." *Annual Review of Sociology* 38:93–118.

Doreian, Patrick, Klaus Teuter, and Chi-Hsien Wang. 1984. "Network Autocorrelation Models: Some Monte Carlo Results." *Sociological Methods & Research* 13:155–200.

Durlauf, Steven N. and Yannis M. Ioannides. 2010. "Social Interactions." *Annual Review of Economics* 2:451–478.

European Central Bank. 2009. "Housing Finance in the Euro Area." Technical report, European Central Bank, Frankfurt.

Fama, Eugene F. 2014. "Two pillars of asset pricing." *American Economic Review* 104:1467–1485.

Fernández de Lis, Santiago and Alicia García Herrero. 2008. "The Housing Boom and Bust in Spain: Impact of the Securitization Model and Dynamic Provisioning." *Housing Finance International* pp. 14–19.

Fligstein, Neil. 1985. "The Spread of the Multidivisional Form Among Large Firms, 1919-1979." *American Sociological Review* 50:377.

Fonseca Diaz, Ana Rosa. 2005. "El gobierno de las cajas de ahorros: influencia sobre la eficiencia y el riesgo." *Universia Business Review* 8:24–37.

Goldstein, Adam and Neil Fligstein. 2017. "Financial markets as production markets: the industrial roots of the mortgage meltdown." *Socio-Economic Review* 15.

Granovetter, Mark. 1978. "Threshold Models of Collective Behavior." *The American Journal of Sociology* 83:1420–1443.

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91:481–510.

Haveman, Heather A. and Lynn Nonnemaker. 2000. "Competition in Multiple Geographic Markets: The Impact on Growth and Market Entry." *Administrative Science Quarterly* 45:232.

Hays, Jude C., Aya Kachi, and Robert J. Franzese. 2010. "A spatial model incorporating dynamic, endogenous network interdependence: A political science application." *Statistical Methodology* 7:406–428.

Hedström, Peter. 1994. "Contagious Collectivities : On the Spatial Diffusion of Swedish Trade Unions , 1890-1940." *American Journal of Sociology* 99:1157–1179.

Kaminska, Izabella. 2009. "Forget Latvia, what about Spain?"

Kaustia, Markku and Samuli Knüpfer. 2012. "Peer performance and stock market entry." *Journal of Financial Economics* 104:321–338.

Keynes, John Maynard. 1936. *The General Theory of Employment, Interest and Money*. London: Macmillan.

Kindleberger, Charles P. and Robert Z. Aliber. 2011. *Manias, Panics and Crashes: A History of Financial Crises, Sixth Edition*. Palgrave Macmillan.

Lavezzolo, Sebastian. 2014. "The Politics of Banking. The Electoral Incentives of Government-Controlled Banks. The Case of Spanish Cajas." *Ph.D. Dissertation in Political Science, New York University* .

Leenders, Roger Th A J. 2002. “Modeling social influence through network autocorrelation: Constructing the weight matrix.” *Social Networks* 24:21–47.

Levenfeld, Gustavo and Eduardo Sanchez. 1988. “Developments in the Spanish mortgage market.” *Housing Finance International* .

Lieberman, Marvin B. and Shigeru Asaba. 2006. “Why do firms imitate each other?” *Academy of Management Review* 31:366–385.

MacKenzie, Donald. 2009. *Material Markets: How Economic Agents are Constructed*. Oxford: Oxford University Press.

MacKenzie, Donald. 2011. “The Credit Crisis as a Problem in the Sociology of Knowledge.” *American Journal of Sociology* 116:1778–1841.

Manski, Charles F. 2000. “Economic Analysis of Social Interactions.” *Journal of Economic Perspectives* 14:115–136.

Marsden, Peter and Noah Friedkin. 1993. “Network Studies of Social Influence.” *Sociological Methods & Research* 22:127–151.

Martín Martín, María del Rosario. 2014. “Análisis de los fondos de titulización españoles: características en el momento de su constitución y comportamiento durante los años de la crisis.”

Merton, Robert King. 1968. *Social theory and social structure*. New York: The Free Press.

Mizruchi, M. S., L. B. Stearns, and Christopher Marquis. 2006. “The Conditional Nature of Embeddedness: A Study of Borrowing by Large U.S. Firms, 1973-1994.” *American Sociological Review* 71:310–333.

Otero González, Luis, Miguel Ezcurra Pérez, Onofre Martorell Cunil, and Carlos Mulet Forteza. 2013. “Análisis del impacto de la titulización hipotecaria en la estabilidad financiera del sistema bancario español.” *Revista Española de Financiación y Contabilidad* 42:513–534.

Powell, Walter W. 1990. “Neither Market nor hierarchy.” *Research in Organizational Behavior* 12:295–336.

Quinn, Sarah L. 2019. *American bonds : how credit markets shaped a nation*. Princeton: Princeton University Press.

Scharfstein, D. S. and J. C. Stein. 1990. “Herd behavior and investment.” *American Economic Review* 80:465–479.

Shalizi, Cosma Rohilla and Andrew C. Thomas. 2011. “Homophily and contagion are generically confounded in observational social network studies.” *Sociological Methods and Research* 40:211–239.

Shiller, Robert J. 1984. “Stock Prices and Social Dynamics.” *Brookings Papers on Economic Activity* 2:457–510.

Shiller, Robert J. 2015. *Irrational Exuberance*. Princeton University Press.

Shleifer, Andrei. 2000. *Inefficient markets : an introduction to behavioral finance*. Oxford University Press.

Slez, Adam. 2016. "mstaR."

Stark, David and Balazs Vedres. 2012. "Political Holes in the Economy." *American Sociological Review* 77:700–722.

Strang, David and Sarah A. Soule. 1998. "Diffusion in Organizations and Social Movements: From Hybrid Corn to Poison Pills." *Annual Review of Sociology* 24:265–290.

Strang, David and Nancy Brandon Tuma. 1993. "Spatial and Temporal Heterogeneity in Diffusion." *American Journal of Sociology* 99:614–639.

Valente, Thomas W. 2005. "Network Models and Methods for Studying the Diffusion of Innovations." In *Models and Methods in Social Network Analysis*, edited by Peter Carrington, John Scott, and Stanley Wasserman, pp. 98–116. Cambrdige University Press.

Wang, Dan J. and Sarah A. Soule. 2012. "Social Movement Organizational Collaboration: Networks of Learning and the Diffusion of Protest Tactics, 1960-1995." *American Journal of Sociology* 117:1674–1722.

White, Harrison C. 2002. *Markets from networks : socioeconomic models of production*. Princeton: Princeton University Press.