Online Appendix for "The Financial Transmission of Housing Booms: Evidence from Spain"

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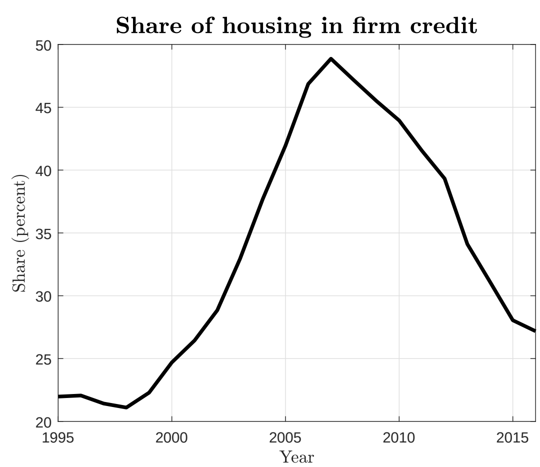
A Data Appendix

A.1 Data sources for Section 1.1

Nominal house prices are taken from the Spanish Ministry of Construction (http://www.fomento.gob.es/MFOM/LANG_CASTELLANO/ATENCION_CIUDADANO/INFORMACION_ESTADISTICA/Vivienda/Estadisticas). We use the series "valor tasado de vivienda libre" (Table 1). Prices are defined as the average price per square meter of free (that is, non-subsidized) housing, and estimated every trimester by the ministry on the basis of data provided by valuation experts. We take a simple average to aggregate this data to a yearly series. The ministry also provides an estimate of the number of new housing construction projects started in a given year ("Numero de viviendas libres iniciadas", Table 3.1). New construction projects also explode during the boom, going from 250'000 in 1997 to around 660'000 in 2006. They then collapse spectacularly, falling below 100'000 in 2009, and below 50'000 in 2012, 2013 and 2014.

Annual GDP data is taken from Eurostat. Finally, data on credit and credit composition is taken from Table 8.9 of the Bank of Spain's Economic Bulletin (https://www.bde.es/webbde/es/estadis/infoest/bolest.html). Throughout, we abstract from credit to non-profits (*Crédito para financiación a instituciones privadas sin fines de lucro*) and "other not elsewhere classified" credit (*Otros sectores residentes sin clasificar*), which represent only a tiny fraction of overall credit. We define housing credit as the sum of credit to construction firms (*Construcción*), credit to real estate firms (*Actividades inmobiliarias*) and mortgage and home improvement credit (*Adquisición y rehabilitación de viviendas*). Deflating credit growth with the EU KLEMS GDP deflator for the market economy, we obtain the growth rates cited in Footnote 8.[1]

Figure A.1: Composition of firm credit, 1995-2016



Source: Bank of Spain.

[1]To be consistent with our micro-level analysis, we construct the credit composition series shown in Figure 2 using CIR data, and not the data from the Bank of Spain's Economic Bulletin (EB). Both series are very close to each other: the share of housing in total credit in 2000 is 46.6% in the CIR and 45.2% in the EB. In 2007, it is 61.9% in the CIR and 61.4% in the EB.

Finally, Figure A.1 plots the share of housing in firm credit (i.e., the share of firm credit going to construction and real estate firms). As stated in Footnote 8, the composition change for firm credit during the housing boom is even more striking than the one for overall credit.

A.2 Summary statistics

Table A.1 contains summary statistics for most variables used in our analysis.

Table A.1: Summary statistics

	Mean	Std. Dev.	25th pctile	Median	75th pctile	# obs.	Year
Panel 1: Bank-firm variables							
$\text{Credit\_growth}^b_{f,2003,2001}$	9.996	74.80	−35.27	−6.353	24.86	582,887	2001-2003
Length of firm-bank relat. (months)	31.69	23.70	12.00	36.00	60.00	845,975	2001
Past defaults	0.126	0.332	0	0	0	845,975	2001
$\text{Credit\_growth}^b_{f,2007,2004}$	16.49	84.48	−39.34	−9.003	48.56	617,748	2004-2007
Length of firm-bank relat. (months)	43.76	35.69	12.00	36.00	84	1.013e+06	2004
Past defaults	0.100	0.301	0	0	0	1.013e+06	2004
Panel 2: Bank variables							
Boom exposure (E^b_{2000})	0.422	0.150	0.333	0.415	0.529	156	2000
Liquidity ratio	0.129	0.0987	0.0460	0.116	0.189	197	2000
Capital ratio	0.126	0.182	0.0560	0.0753	0.107	197	2000
Default rate	0.00932	0.0140	0.00310	0.00623	0.0108	197	2000
ln (Total Assets)	13.17	2.286	11.49	13.27	14.91	197	2000
Panel 3: Firm variables							
$\text{Credit\_growth}_{f,2003,2001}$	16.35	79.66	−34.25	−6.353	41.56	383,607	2001-2003
Firm exposure ($E_{f,2001}$)	0.458	0.103	0.373	0.454	0.529	482,356	2001
Demand shock	−0.151	1.024	−0.568	−0.383	−0.137	391,143	2001
Total assets (thousands euros)	1,596	4,460	154.9	382.8	1,072	226,966	2001
Number employees	20.24	266.6	3	6	14	226,966	2001
Own funds over total assets	0.381	0.278	0.140	0.330	0.590	226,966	2001
Return on assets	0.0249	0.140	−0.00194	0.0234	0.0703	226,955	2001
Young firm dummy (age< 3 years)	0.0552	0.228	0	0	0	226,966	2001
Exporter dummy	0.0658	0.248	0	0	0	226,966	2001
$\text{Credit\_growth}_{f,2007,2004}$	26.63	90.92	−38.23	−9.003	76.68	424,613	2004-2007
Firm exposure ($E_{f,2004}$)	0.457	0.106	0.362	0.454	0.529	578,218	2004
Demand shock	0.830	1.035	0.390	0.588	0.844	460,804	2004
Total assets (thousands euros)	1,680	4,511	161.2	410.3	1,171	318,025	2004
Number employees	17.24	210.9	3	6	12	318,025	2004
Own funds over total assets	0.390	0.288	0.137	0.337	0.613	318,025	2004
Return on assets	0.0205	0.152	−0.00512	0.0207	0.0673	318,016	2004
Young firm dummy (age< 3 years)	0.0614	0.240	0	0	0	318,025	2004
Exporter dummy	0.0514	0.221	0	0	0	318,025	2004

A.3 Additional results and robustness checks

A.3.1 Bank fixed effects

In this section, we introduce bank fixed effects in our loan-level regressions, by estimating

$$\text{Credit\_growth}^b_{f,t} = \beta_1 D_{2002-2003,t}\mathrm{E}^b_{2000} + \beta_2 D_{2005-2008,t}\mathrm{E}^b_{2000} + \mu_b + \mu_{f,t} + u^b_{f,t}, \tag{A.1}$$

where $\text{Credit\_growth}^b_{f,t}$ stands for the growth rate of the credit of non-housing firm f with bank b between year $t-1$ and year t. μ_b are bank fixed effects and $\mu_{f,t}$ are firm-time fixed effects. Finally, $D_{2002-2003,t}$ is a dummy equal to one if the year t is between 2002 and 2003, and $D_{2005-2008,t}$ is defined analogously. We estimate this equation for $t \in \{2002, 2003, ..., 2008\}$, i.e., for annual credit growth rates between 2001 and 2008 (the same time period as in Figures 3 and 4).

Column (1) of Table A.2 shows that crowding-out and crowding-in patterns are preserved: in 2001-2002 and 2002-2003, non-housing credit growth is lower at more exposed banks (with respect to the average non-housing credit growth at the bank over the entire period 2001-2008). Conversely, during 2004-2008, non-housing credit growth is higher at more exposed banks.[2] Column (2) shows that results are preserved when introducing bank controls interacted with the same subperiod dummies. Finally, Columns (3)-(6) replace firm-time fixed effects by firm controls, both for the full sample and for the sample of multibank firms.

Table A.2: Bank exposure and loan-level non-housing credit growth, bank fixed effects

	Firm fixed effects		Firm controls		Firm controls (multib.)	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{2002-2003}\mathrm{E}^b_{2000}$	-1.43	-1.58	-1.90	-1.77	-1.79	-1.70
(s.e.)	(0.52)	(0.58)	(0.34)	(0.55)	(0.42)	(0.59)
$D_{2005-2008}\mathrm{E}^b_{2000}$	2.49	2.27	1.75	1.67	1.96	1.88
(s.e.)	(0.74)	(0.61)	(0.73)	(0.62)	(0.72)	(0.59)
Average dep. variable	7.84	7.84	9.52	9.52	10.24	10.24
Firm-time FE	YES	YES	NO	NO	NO	NO
Bank FE	YES	YES	YES	YES	YES	YES
Firm controls	NO	NO	YES	YES	YES	YES
Bank controls	NO	YES	NO	YES	NO	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
Ind.×munic. FE	NO	NO	YES	YES	YES	YES
Balance-sheet data	NO	NO	YES	YES	YES	YES
R-sq	0.40	0.41	0.26	0.26	0.27	0.27
# observations	2,621,396	2,621,396	2,437,477	2,437,477	1,977,966	1,977,966
# firms	251,646	251,646	366,560	366,560	233,662	233,662
# banks	137	137	137	137	137	137

Notes: All regressions are based on Equation (A.1), estimated by WLS. Bank exposure (E^b_{2000}) is measured by the share of housing loans in total bank loans in 2000, and normalized to have zero mean and unit variance. Columns (1)-(2) and (5)-(6) are estimated for a sample of firms which borrow from at least two banks (multibank firms). Bank, firm and firm-bank controls are listed in Table 1. Standard errors multi-clustered at the bank and firm level are shown in parentheses.

[2] Our results are unchanged if we instead consider a dummy for the period 2004-2007.

A.3.2 Pretrend regressions

As discussed in the main text, our sample starts in the year 2000, because of the merger wave in the Spanish banking system in the late 1990s. Even though the bulk of the increase in house prices took place after 2000 (see Figure 1), one could still worry that the housing boom had already started earlier. In this section, we examine this concern by reducing our sample to banks which were unaffected by mergers and acquisitions, and estimating our basic loan-level regression given in Equation (2) for the periods 1996-1998 and 1998-2000. As Table A.3 shows, our point estimates for these regressions are close to zero and insignificant. This indicates that there were no pretrends: exposure had no effect on non-housing credit growth before the housing boom started in earnest.

Table A.3: Bank exposure and loan-level non-housing credit growth, pretrend regressions

	Firm fixed effects		Firm controls		Firm controls (multib.)	
	1996-1998	1998-2000	1996-1998	1998-2000	1996-1998	1998-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure (E^b_{2000})	−0.14	1.11	0.01	0.05	−0.03	0.25
(s.e.)	(1.38)	(1.19)	(1.39)	(1.06)	(1.45)	(1.13)
Average dep. variable	19.39	13.76	27.49	18.13	27.82	19.07
Firm fixed effects	YES	YES	NO	NO	NO	NO
Firm controls	NO	NO	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
Ind. × munic. FE	NO	NO	YES	YES	YES	YES
Balance-sheet data	NO	NO	YES	YES	YES	YES
R-sq	0.55	0.53	0.45	0.43	0.45	0.43
# observations	76,621	95,051	56,627	84,023	50,377	71,993
# firms	31,719	39,134	33,674	51,758	27,424	39,728
# banks	103	103	103	103	103	103

Notes: All results are based on Equation (2), and consider a sample of banks that were not affected by the merger wave of the late 1990s. See Table 1 for further details.

A.3.3 Alternative measures of housing exposure

Our baseline results use the share of bank credit going to housing in 2000 as a proxy for their exposure to the housing boom. In this section, we consider two alternative proxies.

First, we follow Chakraborty et al. (2018) and consider the geographical distribution of bank activity, assuming that banks are more exposed if they operate in municipalities that are prone to stronger housing booms. To generate an exogenous source of variation in housing prices, we rely on municipal housing supply elasticities (HSEs), which were first introduced by Saiz (2010) for the United States, and by Basco and Lopez-Rodriguez (2017) for Spain. More precisely, we measure land unavailability (which can be seen as the inverse of HSE), defined as the ratio of built urban surface over the potential plot surface, and computed using census data from the Spanish Cadastre (Catastro) in the year 2000.[3] We then define a bank-specific exposure measure as

$$\mathrm{E}_{2000}^{b,LU} = \sum_{m} \omega_{m,2000}^{b} LU_{m,2000}, \tag{A.2}$$

where $\omega_{m,2000}^{b}$ refers to the share of total credit of bank b in municipality m[4] and $LU_{m,2000}$ is the land unavailability ratio for municipality m in 2000. This measure is expected to be positively associated with the housing boom, as municipalities with less available land should have higher housing price increases. The average value of the land availability measure is 0.053, and its standard deviation is 0.204.

Table A.4 reports the estimates for this alternative exposure measure, using our baseline specification given by Equation (2). The structure of Table A.4 is analogous to that of Table 1 and the estimated effects are also similar, albeit smaller in magnitude and somewhat less significant.

Table A.4: Bank exposure and loan-level non-housing credit growth, geographical exposure

	Firm fixed effects		Firm controls		Firm controls (multib.)	
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure ($\mathrm{E}_{2000}^{b,LU}$)	−1.28	2.92	−1.34	2.71	−1.48	2.66
(s.e.)	(0.81)	(1.23)	(0.81)	(1.13)	(0.87)	(1.22)
Average dep. variable	11.80	17.46	15.96	20.89	17.02	21.97
Firm fixed effects	YES	YES	NO	NO	NO	NO
Firm controls	NO	NO	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
Ind. × munic. FE	NO	NO	YES	YES	YES	YES
Balance-sheet data	NO	NO	YES	YES	YES	YES
R-sq	0.48	0.50	0.34	0.34	0.35	0.35
# observations	276,839	247,153	243,452	247,529	202,801	201,523
# firms	97,353	85,878	124,594	130,552	83,943	84,546
# banks	132	127	132	127	132	127

Notes: See notes to Table 1. Bank exposure is measured by the land unavailability ratio defined in Equation (A.2).

Second, we can also measure banks' exposure by their ratio of mortgage-backed credit over total credit in 2000. Table A.5 shows that our results are preserved under this alternative measure.

[3] Potential plot surface includes all available land for construction. It excludes protected non-urban areas (e.g. rivers or natural parks) and public goods land (e.g. local surface covered by transport infrastructure and utilities).

[4] This share can be constructed by matching the CIR to our firm-level data, which includes zipcodes of firms' headquarters.

Table A.5: Bank exposure and loan-level non-housing credit growth, Mortgage-backed exposure

	Firm fixed effects		Firm controls		Firm controls (multib.)	
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure ($E_{2000}^{b,MG}$)	-2.00	4.02	-1.69	3.89	-1.85	3.86
(s.e.)	(0.95)	(1.20)	(0.90)	(0.99)	(0.97)	(1.07)
Average dep. variable	11.79	17.46	15.94	20.88	17.00	21.97
Firm fixed effects	YES	YES	NO	NO	NO	NO
Firm controls	NO	NO	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
Ind. × munic. FE	NO	NO	YES	YES	YES	YES
Balance-sheet data	NO	NO	YES	YES	YES	YES
R-sq	0.48	0.50	0.34	0.34	0.35	0.35
# observations	277,280	247,578	243,867	247,971	203,106	201,813
# firms	97,501	86,027	124,795	130,798	84,034	84,640
# banks	152	145	137	137	137	137

Notes: See notes to Table 1. Bank exposure is measured by the ratio of mortgage-backed credit to total credit in 2000.

A.3.4 Sample without public savings banks

Public savings banks (*cajas*) represented a large share of overall credit in Spain during the housing boom, and expanded substantially during the period. However, they operated under a different institutional framework than "regular" commercial banks, and were often controlled by local politicians (see Santos, 2017a). Moreover, they were also on average more exposed to housing than commercial banks. Table A.6 presents our baseline estimates in a sample without public savings banks. Results are even stronger than in the full sample, showing that public savings banks do not drive our results.

Table A.6: Bank exposure and loan-level non-housing credit growth, sample without savings banks

	Firm fixed effects		Firm controls		Firm controls (multib.)	
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure (E^b_{2000})	−3.95	6.12	−3.47	6.17	−3.72	6.23
(s.e.)	(1.30)	(1.33)	(1.21)	(1.28)	(1.29)	(1.29)
Average dep. variable	13.51	19.15	17.74	21.80	18.94	22.82
Firm fixed effects	YES	YES	NO	NO	NO	NO
Firm controls	NO	NO	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
Ind. × munic. FE	NO	NO	YES	YES	YES	YES
Balance-sheet data	NO	NO	YES	YES	YES	YES
R-sq	0.53	0.54	0.39	0.38	0.40	0.39
# observations	159,300	139,322	153,559	159,089	127,982	129,176
# firms	60,361	52,228	88,100	93,911	62,523	63,998
# banks	33	30	33	30	33	30

Notes: See notes to Table 1. We exclude public savings banks (*cajas*) from the sample.

A.3.5 Geographical clustering

Table A.7 shows our results when estimating Equation (2) for three different subsamples: a sample of national banks (defined as banks operating in at least 15 of Spain's 50 provinces), a sample of non-housing firms located in the 25 provinces that experienced the highest growth in house prices between 2000 and 2007, and a sample of non-housing firms located in the remaining 25 provinces. Our baseline results hold in all three subsamples.

Table A.7: The role of geographical clustering

	National banks		High housing price growth		Low housing price growth	
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure (E^b_{2000})	−3.12	5.21	−2.66	3.66	−1.97	7.25
(s.e.)	(0.97)	(1.26)	(1.28)	(1.41)	(1.15)	(1.45)
Average dep. variable	11.90	17.68	18.08	21.56	15.34	21.64
Firm fixed effects	YES	YES	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES	YES	YES
R-sq	0.49	0.51	0.46	0.49	0.47	0.50
# observations	252,613	225,303	101,545	97,566	55,443	60,636
# firms	89,549	78,943	33,906	32,354	19,303	20,680
# banks	53	54	129	123	104	96

Notes: The table reports estimates from Equation (2) for different subsamples. National banks are those operating in more than 15 provinces. Columns (3) and (4) limit the sample to firms located in the 25 provinces with the highest housing price growth between 2000 and 2007, while columns (5) and (6) limit the sample to the remaining 25 provinces. See notes to Table 1 for further details.

A.3.6 The extensive margin of credit

To account for the extensive margin of credit growth, we first follow Chodorow-Reich (2014) and consider a measure of credit growth of firm f with bank b between year t_0 and year t_1 that incorporates the creation of new lending relationships and the termination of existent loans:

$$\text{Extensive\_Credit\_growth}^{b}_{f,t_0,t_1} = 100 \cdot \frac{q^{b}_{f,t_1} - q^{b}_{f,t_0}}{0.5 \cdot (q^{b}_{f,t_1} + q^{b}_{f,t_0})} \tag{A.3}$$

This definition yields a growth measure that is symmetric around zero and bounded between -200 and 200, providing an integrated treatment of new loans, ended loans, and continuing loans. Second, we analyze how banks' boom exposure affects the probability of creating a new credit relationship by considering as dependent variable a dummy that takes the value one if a given bank-firm (loan) pair was not active in year t_0 but it is active in year t_1 ($\text{New\_loan}^{b}_{f,t_0,t_1}$).

Table A.8 presents the results for the two subperiods 2001-2003 and 2004-2007, using our baseline exposure measure. Columns (1)-(2) consider the extensive-margin growth rate defined in Equation (A.3) as dependent variable. The crowding-out estimate in column (1) is similar to that of Table 1, albeit less significant. On the other hand, the crowding-in estimate for the 2004-2007 period is somewhat larger than in the baseline. Columns (3)-(4) in Table A.8 consider New_loan as the dependent variable. Banks more exposed to the boom are less likely to start a new lending relationship with non-housing firms in the 2001-2003 period, even though the point estimate is only marginally significant. In contrast, those banks are significantly more likely to do so between 2004 and 2007.

Table A.8: Bank exposure and loan-level non-housing credit growth, the extensive margin

	Extensive_Credit_growth		New_loan	
	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)
Bank exposure (E^{b}_{2000})	-2.63	9.58	-0.006	0.02
(s.e.)	(-1.83)	(1.26)	(0.004)	(0.004)
Average dep. variable	6.79	18.08	0.27	0.37
Firm fixed effects	YES	YES	YES	YES
Firm controls	NO	NO	NO	NO
Bank controls	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES
Ind. × munic. FE	NO	NO	NO	NO
Balance-sheet data	NO	NO	NO	NO
R-sq	0.51	0.68	0.58	0.69
# observations	610,413	803,718	610,413	803,718
# firms	196,644	251,971	196,644	251,971
# banks	135	129	135	129

Notes: See notes to Table 1.

A.3.7 The Spanish banking crisis

In this section, we present some results for the period 2008-2011, when the Spanish housing boom had given way to a severe banking crisis. We end our analysis in 2011, as the resolution of the crisis lead to a large amount of mergers and bank failures (see Santos, 2017b) which make it difficult to track bank identities beyond that year.

Table A.9 shows the results of our baseline loan-level regressions for the banking crisis period. It is the equivalent of Table 1 in the main text, for the time period 2008-2011. The results indicate a large negative effect of housing exposure: during the banking crisis, the same non-housing firm had substantially lower credit growth at more exposed banks.

Table A.9: Bank exposure and loan-level non-housing credit growth, banking crisis

	Firm fixed effects 2008-2011	Firm controls 2008-2011	Firm controls (multib.) 2008-2011
	(1)	(2)	(3)
Bank exposure (E^b_{2000})	-7.51	-7.59	-7.63
(s.e.)	(1.97)	(1.85)	(1.89)
Average dep. variable	5.74	8.53	9.02
Firm fixed effects	YES	NO	NO
Firm controls	NO	YES	YES
Bank controls	YES	YES	YES
Firm-bank controls	YES	YES	YES
Ind.×munic. FE	NO	YES	YES
Balance-sheet data	NO	YES	YES
R-sq	0.46	0.34	0.35
# observations	217,793	205,180	163,274
# banks	85	85	85

Notes: see Table 1.

Table A.10 shows the results of our baseline firm-level regression for the banking crisis period. It is the equivalent of Table 3 in the main text, for the time period 2008-2011. Again, we find a large negative effect of exposure: firms that are more exposed to exposed banks see substantially larger contractions in credit during the banking crisis years.

Overall, these results indicate that the end of the housing boom disproportionately affected banks that were more exposed to housing, and that firms with stronger links to these banks suffered. These results are very much in line with the existing evidence on the Spanish banking crisis (see Bentolila et al., 2017; Santos, 2017b). They are also very much in line with our emphasis on financial transmission. Indeed, the negative effect of exposure during the crisis is consistent with our model, assuming that the banking crisis triggered a large fall in the net worth of banks that were more exposed to housing. However, studying this effect more comprehensively (and quantifying it) is beyond the scope of our paper.

Table A.10: Boom exposure and credit growth at the firm level, banking crisis

	All firms 2008-2011	Multibank firms 2008-2011
	(1)	(2)
Firm exposure (E_{f,t_0})	-5.33	-5.87
(s.e.)	(0.98)	(1.31)
Average dep. variable	11.20	16.03
Firm controls	YES	YES
Firm-bank controls	YES	YES
Industry × municipality FE	YES	YES
Balance-sheet data	YES	YES
R-sq	0.53	0.53
# observations	96,776	53,773

Notes: See Table 3.

A.3.8 Robustness of firm-level results to alternative boom exposure measures

Table A.11 reports the results for our baseline firm-level regression (specified in Equation (4)) when using the geographical exposure measure defined in Appendix A.3.3. That is, we still compute firm exposure according to Equation (3), but the bank exposure measure E^{b}_{2000} is substituted by $E^{b,LU}_{2000}$. Estimates are similar to our baseline results shown in the main text.

Table A.11: Boom exposure and credit growth at the firm level, alternative exposure measure

	All firms		Multibank firms	
	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)
Firm exposure (E^{LU}_{f,t_0})	-1.94	3.00	-2.94	2.69
(s.e.)	(1.22)	(1.56)	(1.41)	(1.75)
Average dep. variable	23.04	31.05	32.94	43.39
Firm controls	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES
Industry × municipality FE	YES	YES	YES	YES
Balance-sheet data	YES	YES	YES	YES
R-sq	0.57	0.55	0.58	0.55
# observations	82,401	96,799	48,944	54,950

Notes: All regressions are based on Equation (4). Firm exposure is standardized to have zero mean and unit variance. Firm controls are total assets, number of employees, own funds over total assets, return on assets, a dummy for firms younger than three years, and a dummy for exporters. Standard errors multi-clustered at the main bank and industry-municipality level in parentheses.

A.3.9 Further results for cash-flow loans

Table A.12 reproduces Table 5 for the sample of cash-flow loans.

Table A.12: Bank exposure, constrained versus unconstrained banks, cash-flow loans

	2001-2003		2004-2007	
	Constrained	Unconstrained	Constrained	Unconstrained
	(1)	(2)	(3)	(4)
Bank exposure (E^b_{2000})	−3.43	5.93	2.20	1.89
(s.e.)	(0.71)	(2.90)	(1.53)	(4.27)
Average dep. variable	6.47	3.49	17.08	13.75
Firm fixed effects	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES
Firm-bank controls	YES	YES	YES	YES
Multiple banks per firm	YES	YES	YES	YES
R-sq	0.51	0.62	0.55	0.64
# observations	96,833	5,323	100,697	3,798
# firms	37,582	2,584	38,370	1,839
# banks	58	19	56	18

Notes: All regressions are based on Equation (2). Unconstrained banks are banks in the lowest quartile of the bank leverage ratio in the first year of the period, constrained banks are all others. Standard errors in parentheses.

A.3.10 Further alternative explanations for the crowding-in effect

Table A.13 shows the results of our analysis using credit supply shocks identified with the Amiti and Weinstein (2018) methodology. Table A.14 introduces securitization controls into our regression of net worth growth on bank exposure to the housing boom.

Table A.13: Bank exposure and securitization: Credit supply analysis

Dep. variable is bank credit supply identified based on Amiti and Weinstein (2018)						
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
Bank exposure (E^b_{2000})	−0.30	0.38	−0.30	0.32	−0.30	0.29
(s.e.)	(0.12)	(0.10)	(0.13)	(0.12)	(0.13)	(0.11)
Securitization level			0.03	0.25		
(s.e.)			(0.53)	(0.25)		
Securitization change					−0.12	0.77
(s.e.)					(0.96)	(0.40)
R-sq	0.15	0.23	0.15	0.24	0.15	0.26
# observations	136	130	136	130	136	130

Notes: Bank exposure (E^b_{2000}) is measured by the share of housing loans in total bank loans in 2000. Securitization is measured as the ratio of asset backed securities (ABS) and covered bonds over total assets in the first year of the period. Bank controls are the natural logarithm of total assets, capital ratio, liquidity ratio, and default rate. Standard errors in parentheses.

Table A.14: Bank exposure and net worth growth: controlling for securitization

Dep. variable is growth in bank net worth						
	2001-2003	2004-2007	2001-2003	2004-2007	2001-2003	2004-2007
	(1)	(2)	(4)	(5)	(7)	(8)
Bank exposure (E^b_{2000})	0.07	0.63	0.10	0.59	0.07	0.58
(s.e.)	(0.09)	(0.12)	(0.10)	(0.15)	(0.10)	(0.14)
Securitization level			−0.56	0.12		
(s.e.)			(0.43)	(0.29)		
Securitization change					−0.33	0.38
(s.e.)					(0.78)	(0.48)
R-sq	0.45	0.62	0.45	0.62	0.45	0.62
# observations	140	136	140	136	140	136

Notes: Bank boom exposure (E^b_{2000}) is measured by the share of housing loans in total bank loans in 2000. Securitization is measured as the ratio of asset backed securities (ABS) and covered bonds over total assets in the first year of the period. Bank controls are the natural logarithm of total assets, capital ratio, liquidity ratio, and default rate, measured in the initial year of the period. Standard errors in parentheses.

B Model Appendix

B.1 Further details on the model and the calibration

B.1.1 Additional derivations

Credit demand In every period t, firm ω from sector j demands credit from the B banks in the economy. To pay for this credit, the firm promises each bank b a fraction $m_{j,t+1}^{b}(\omega)$ of its capital income in period $t+1$. Therefore, the cost minimization problem of the firm is given by

$$\begin{aligned}
&\min_{m_{j,t+1}^{b}(\omega)} \left(\mathbb{E}_t\left(\textstyle\sum_{b=1}^{B} m_{j,t+1}^{b}(\omega)\, p_{j,t+1}^{K}(\omega)\, k_{j,t+1}(\omega)\right)\right)\\
&\text{such that}\quad k_{j,t+1}(\omega) = \left(\textstyle\sum_{b=1}^{B}\left(\pi_j^b(\omega)\right)^{\frac{1}{\eta_j}}\left(q_{j,t}^{b}(\omega)\right)^{\frac{\eta_j}{\eta_j-1}}\right)^{\frac{\eta_j}{\eta_j-1}},\\
&\forall b,\ \mathbb{E}_t\left(\frac{m_{j,t+1}^{b}(\omega)p_{j,t+1}^{K}(\omega)k_{j,t+1}(\omega)}{q_{j,t}^{b}(\omega)}\right) = R_{t+1}^{b},\\
&\textstyle\sum_{b=1}^{B} m_{j,t+1}^{b}(\omega) \leq 1.
\end{aligned} \tag{A.4}$$

That is, firms minimize the expected amount of resources they need to pay to banks tomorrow, subject to three constraints: their capital tomorrow is given by the production function, the expected return on a credit contract with bank b must be equal to R_{t+1}^{b}, and they cannot promise more than their income. Note that because of perfect competition, firms take the expected future price of their product and the expected returns requested by banks as given.

The constraint on required returns for each bank b implies that $\mathbb{E}_t\left(m_{j,t+1}^{b}(\omega)\, p_{j,t+1}^{K}(\omega)\, k_{j,t+1}(\omega)\right) = R_{t+1}^{b} q_{j,t}^{b}(\omega)$. Therefore, we can substitute this constraint into the objective function, and obtain the problem shown in Equation (12) in the main text. That problem omits the constraint that firms cannot promise more than their income, but it is easy to verify that this always holds (see next paragraph).

Credit repayments From the above, it is easy to see that the fraction of future income promised by firm ω of sector j to bank b holds

$$m_{j,t+1}^{b}(\omega) = \frac{R_{t+1}^{b} q_{j,t}^{b}(\omega)}{\mathbb{E}_t\left(p_{j,t+1}^{K}(\omega)\right) k_{j,t+1}(\omega)}. \tag{A.5}$$

Summing across all banks, we get

$$\sum_{b=1}^{B} m_{j,t+1}^{b}(\omega) = \frac{\sum_{b=1}^{B} R_{t+1}^{b} q_{j,t}^{b}(\omega)}{\mathbb{E}_t\left(p_{j,t+1}^{K}(\omega)\right) k_{j,t+1}(\omega)}. \tag{A.6}$$

The numerator of this expression is the total cost of credit of firm ω of sector j. By definition of the firm's marginal cost (the firm's ideal price index for credit), it is equal to $R_{j,t+1}(\omega)\, k_{j,t+1}(\omega)$. Furthermore, as discussed in the main text, perfect competition implies that in equilibrium, $R_{j,t+1}(\omega) = \mathbb{E}_t\left(p_{j,t+1}^{K}(\omega)\right)$. Thus, we finally have $\sum_{b=1}^{B} m_{j,t+1}^{b}(\omega) = 1$. This result is intuitive: because of perfect competition, firms promise their entire future capital income to banks and make no profits.

Finally, using Equation (A.5), it is easy to show that the actual repayment received by bank b in period $t+1$ holds

$$m_{j,t+1}^{b}(\omega)\, p_{j,t+1}^{K}(\omega)\, k_{j,t+1}(\omega) = R_{t+1}^{b} q_{j,t}^{b}(\omega)\, \frac{p_{j,t+1}^{K}(\omega)}{\mathbb{E}_t\left(p_{j,t+1}^{K}(\omega)\right)} = R_{t+1}^{b} q_{j,t}^{b}(\omega)\, \frac{A_{j,t+1}P_{j,t+1}}{\mathbb{E}_t\left(A_{j,t+1}P_{j,t+1}\right)}, \tag{A.7}$$

where we have used Equation (11) and the fact that capital stocks at period $t+1$ are known in period t.

Law of motion of bank net worth Lagging Equation (A.7) by one period, and aggregating across all firms of a given sector, we get that the total repayments of bank b from firms of sector j at time t are given by $R_t^b Q_{j,t-1}^b \frac{A_{j,t}P_{j,t}}{\mathbb{E}_{t-1}(A_{j,t}P_{j,t})}$. Old bankers collect these credit repayments, and pay back the credit that they obtained from the rest of the world. As the financial constraint of bankers is always binding, their total borrowing from the IFM in period $t-1$ is equal to $(\lambda - 1) W_{t-1}^b$. These considerations directly yield the law of motion of bank net worth given in Equation (18) in the main text.

B.1.2 Housing prices and the income of the old

The income of old agents is given by

$$\sum_{j \in \{N,H\}} \left((1-\phi) \left(\alpha_j P_{j,t} Y_{j,t} - R^* Q_{j,t-1} \right) + R^* (1-\alpha_j) P_{j,t-1} Y_{j,t-1} \right). \tag{A.8}$$

This expression is intuitive. The only old agents with a positive income are bankers and workers (as entrepreneurs do not make profits, they have no old-age income). Old bankers collect the economy's entire capital income, repay their loans to the IFM, and keep a fraction $1-\phi$ of their profits (the remainder being paid out to young bankers). Workers save their entire labor income at the international interest rate R^* and collect the proceeds when old.

Throughout the paper, we consider equilibria in which the income of old agents exceeds the value of housing output ($P_{H,t}Y_{H,t}$) in every possible state of the world, implying that $P_{H,t} = \xi_t$ in every state of the world. To impose this condition, we assume that there is an upper bound for housing price increases. Then, it is sufficient to check that for every period t, even if housing prices were to reach their highest possible value, the income of the old would still be higher than the value of housing output.

Note that we have assumed that housing price growth follows an AR(1) process, which implies that housing prices are in principle unbounded. However, we can approximate the stochastic process for housing price growth by a finite-state Markov chain, bounded by definition. We consider an upper bound of 25% per year, substantially higher than the highest realization of housing price growth in our baseline calibration (which is 8.3%).[5]

B.1.3 Balanced growth path solution

We define the balanced growth path (BGP) of our model as the equilibrium that applies when productivity in both sectors grows at a constant rate g_A (i.e., $\frac{A_{H,t}}{A_{H,t-1}} = \frac{A_{N,t}}{A_{N,t-1}} = 1 + g_A$ for every t), and housing preferences are constant over time and normalized to 1 for convenience (i.e., $\xi_t = 1$ for every t). In this section, we show that on the BGP, credit, investment and net worth grow at a constant rate g, while interest rates are constant. For simplicity, we assume $\alpha_N = \alpha_H = \alpha$, as in our calibration.

The BGP equilibrium Using Equation (18), we get that the net worth of bank b on the BGP holds

$$\widehat{W}_t^b = \frac{\phi \widehat{R}^b \left(\widehat{Q}_{N,t-1}^b + \widehat{Q}_{H,t-1}^b \right)}{1 + \frac{\phi R^* (\lambda - 1)}{1+g}},$$

where $\widehat{X}_t$ stands for the BGP value of variable X in period t. Combining this expression with the credit market clearing condition in Equation (17), we get

$$\widehat{R}^b = \frac{1 + g + \phi R^* (\lambda - 1)}{\lambda \phi}. \tag{A.9}$$

[5] An even simpler alternative would be to assume that there is an additional category of agents in the economy that have the same preferences as all others, but receive their income from abroad (e.g., pensioners from Northern Europe). This would not affect any of our results, but by making the income of these agents arbitrarily large, it would be assured from the outset that income is always sufficient to buy housing output.

That is, every bank charges the same interest rate on the BGP. This is a consequence of the linearity of our model: each bank's credit supply is linear in net worth, and net worth is linear in credit demand. As interest rates are constant, Equations (14) to (16) immediately imply that credit for each bank-firm pair, the overall credit of each firm, and aggregate capital grow at rate $g = (1+g_A)^{\frac{1}{1-\alpha}} - 1$.

Finally, Equation (A.9) also provides a necessary and sufficient condition for banks' financial constraints to be binding on the BGP. Indeed, it is straightforward to see that $\widehat{R} > R^*$ iff $\phi < \frac{1+g}{R^*}$. We impose this condition throughout.

Credit shares on the BGP Using Equation (14), we can show that on the BGP, total credit to sector j holds $\widehat{Q}_{j,t} = \left(\frac{\alpha \widehat{A}_{j,t+1}}{\widehat{R}}\right)^{\frac{1}{1-\alpha}}$. Accordingly, the BGP ratio of housing to non-housing credit holds

$$\frac{\widehat{Q}_{H,t}}{\widehat{Q}_{N,t}} = \widehat{\left(\frac{A_H}{A_N}\right)}^{\frac{1}{1-\alpha}}, \tag{A.10}$$

where $\widehat{\frac{A_H}{A_N}}$ is the relative productivity of the non-housing sector (constant on the BGP). For each bank b, the BGP ratio of housing to non-housing credit is

$$\frac{\widehat{Q}^b_{H,t}}{\widehat{Q}^b_{N,t}} = \widehat{\left(\frac{A_H}{A_N}\right)}^{\frac{1}{1-\alpha}} \cdot \frac{\int_0^1 \pi^b_H(\omega)\, d\omega}{\int_0^1 \pi^b_N(\omega)\, d\omega}. \tag{A.11}$$

This expression shows that a bank is more exposed if it is relatively preferred by housing firms with respect to non-housing firms.

Finally, the BGP share of credit of firm ω of sector j coming from bank b simply holds

$$\frac{\widehat{q}^b_{j,t}(\omega)}{\widehat{q}_{j,t}(\omega)} = \pi^b_j(\omega). \tag{A.12}$$

These expressions show that credit shares and exposure measures on the BGP only depend on the relative productivity of both sectors and on the distribution of preference weights $\pi^b_j(\omega)$ across firms.

B.1.4 Parameter values for illustrations

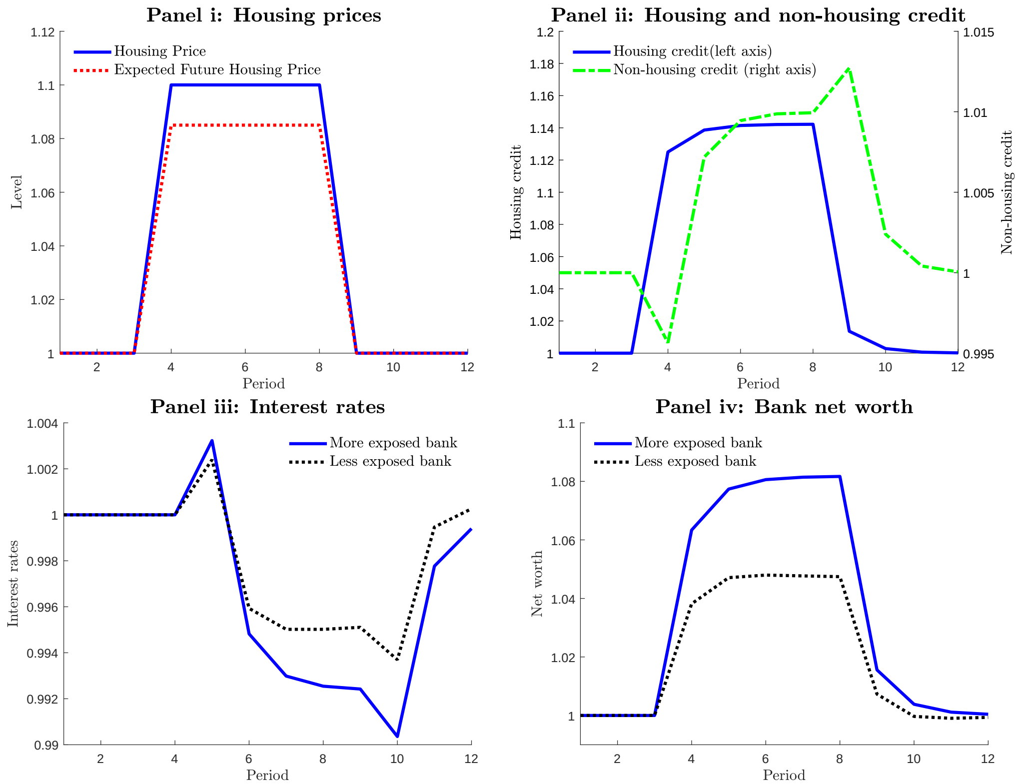
Figure 6 mostly uses the same parameter values as in our baseline calibration, listed in the main text. The only differences with respect to the baseline calibration are that we set $g_A = 0$, and that we consider an arbitrary housing boom. The housing boom shown in Figure 6 consists of five successive periods of increases in the relative price of housing: in the first period, the relative price of housing increases by 5%, and in subsequent periods, it increases by 4%, 3%, 2% and 1%. As stated in the main text, agents perfectly foresee these increases.

B.1.5 A stochastic housing boom

In this section, we briefly illustrate how a stochastic housing boom can trigger a strong crowding-in effect, increasing non-housing credit above its level in the absence of a housing boom.

To do so, we assume that the relative price of housing follows a Markov chain with two possible values, a high and a low one. Figure A.2 illustrates the consequences of a housing boom (a number of periods spent in the state with high housing prices) in this model.

Figure A.2: Illustration: a stochastic housing boom



Notes: These figures illustrate our model's main qualitative predictions for a stochastic housing boom. With the exception of the housing price process, all parameter values are the same as those used for Figure 6 (see Online Appendix B.1.4). We assume that housing prices are 1 in the low state of the world and 1.1 in the high state of the world, that there is a very small probability to transition from the low to the high state of the world, and a 15% probability to transition from the high to the low state of the world.

Figure A.2 shows that this stochastic boom first crowds out non-housing credit and then crowds it in again, exactly as in the illustration discussed in the main text. However, the crowding-in effect of the stochastic boom is stronger: interest rates eventually fall below their pre-boom level (see Panel iii) and non-housing credit rises above its pre-boom level (see Panel ii). Indeed, as the boom has a positive probability of ending every period, expected future housing prices rise less than realized housing prices. However, credit demand is proportional to expected prices, while net worth (and therefore credit supply) is proportional to realized prices. Thus, the credit supply curve eventually shifts out more than the credit demand curve, lowering the equilibrium interest rate and triggering the strong crowding-in effect.

B.2 Details on the calibration

BGP heterogeneity We set the parameters π_H^1, $\theta_{N,A}$, $\theta_{N,B}$ and $\theta_{N,C}$ in order to match the four BGP moments described in the main text (the exposure of both types of banks, and the average and standard deviation of firm exposure). Precisely, we choose the parameter values which minimize the distance function

$$D = \sum_{m=1}^{4} w_m \left(\frac{\text{Moment}_m\,(\text{Data}) - \text{Moment}_m\,(\text{Model})}{0.5 \cdot (\text{Moment}_m\,(\text{Data}) + \text{Moment}_m\,(\text{Model}))} \right)^2, \tag{A.13}$$

where w_m are weights for each moment in the distance function. Given the importance of bank exposure, we set $w_m = 100$ for the two bank exposure measures, and $w_m = 1$ for the remaining two moments. Note, however, that Table 10 shows that we match all four moments almost perfectly, so that these weights do not matter much. Note as well that this part of the calibration is independent of the remainder (as the targeted moments only depend on the four parameters to be calibrated, and the predetermined relative productivity of housing) and can therefore be carried out separately.

Main calibration As described in the main text, our model has four internally calibrated parameters: g_A, ζ, ϕ and η_N. To estimate these parameters, we proceed as follows. First, we impose that the share of housing in total credit in 2007 (which identifies ζ) and the increase in non-housing credit between 2000 and 2007 (which identifies g_A) are matched exactly. That is, we only consider parameter combinations $(g_A, \zeta, \phi , \eta_N)$ for which the model values of these two moments are within 0.05 percentage points of the data targets.[6] For this subset of the parameter space, we minimize the distance function

$$D = \sum_{m=1}^{4} w_m \left(\frac{|\text{Moment}_m\,(\text{Data}) - \text{Moment}_m\,(\text{Model})|}{0.5 \cdot (|\text{Moment}_m\,(\text{Data})| + |\text{Moment}_m\,(\text{Model})|)} \right)^2, \tag{A.14}$$

where the four moments considered are our cross-sectional regression coefficients (as described in the main text) and w_m are weights for each moment in the distance function.[7] We set $w_m = 1$ for the two loan-level coefficients, and $w_m = 2$ for the two firm-level coefficients, reflecting the fact that firm-level results are more informative about aggregate outcomes than bank-level coefficients, and should therefore be matched more closely. We solve this minimization problem using a Differential Evolution algorithm for MATLAB. The algorithm was developed by Markus Buehren and is available for download at https://it.mathworks.com/matlabcentral/fileexchange/18593-differential-evolution. In order to speed up computations, we impose bounds for all 4 parameters to be calibrated, listed in Table A.15. As can be verified from the results, these bounds are not binding, with the exception of one robustness check (see Appendix B.3.5), in which the lower bound on ϕ is binding. However, note that this lower bound is not arbitrary: it is essentially zero, for a parameter that conceptually needs to be positive.

Table A.15: Bounds for the numerical calibration

Parameter	Lower bound	Upper bound
g_A	0.045	0.065
ζ	0.6	0.7
ϕ	0.001	0.15
η_N	0	8

B.3 Robustness checks and additional results

B.3.1 A calibration with three bank types

In the main text, we assume that there are $B = 2$ bank types. In this section, we consider instead the case with $B = 3$ bank types. We assume that the data equivalents of these bank types are banks above the 66th percentile of exposure (type 1), banks between the 33rd and the 66th percentile of exposure (type 2) and banks below the 33rd percentile of exposure (type 3).

Our calibration of the three-bank model closely follows the one of the two-bank model. The only changes apply to the way in which we model firm heterogeneity. We keep assuming that there is only one type of housing firm, with a preference profile $\left(\pi_H^1, \pi_H^2, 1 - \pi_H^1 - \pi_H^2\right)$. However, we now consider seven different

[6] Imposing such a condition is necessary to prevent the estimation procedure from trading off fit across different moments in a situation in which we have more targets (6) than parameters (4). Precisely, we want to avoid that the algorithm chooses e.g. a higher shock size ζ to match the cross-sectional regressions by overpredicting the increase in the housing share of total credit.

[7] Note that absolute values in Equation (A.14) are needed because moments may be either negative or positive.

types of non-housing firms, with preference profiles $(0.95, 0.05, 0)$, $(0, 0.95, 0.05)$, $(0.05, 0, 0.95)$, $(1/2, 1/2, 0)$, $(0, 1/2, 1/2)$, $(1/2, 0, 1/2)$ and $(1/3, 1/3, 1/3)$.[8] We calibrate the parameters π_H^1, π_H^2 and the vector $\boldsymbol{\theta}_N$ (giving the mass of each type of non-housing entrepreneur) in order to match the same moments as in the main text: our boom exposure measure for the three types of banks and the average and standard deviation of our non-housing firm exposure measure.

There are now eight free parameters and five moments to match. Thus, without further restrictions, parameters are not identified. To deal with this, we exogenously set the mass of firms with preferences $(1/2, 1/2, 0)$, $(0, 1/2, 1/2)$ and $(1/2, 0, 1/2)$ to 0.05. Table A.16 summarizes the other parameter values.

Table A.16: Calibrated parameters: bank and firm-level heterogeneity, three-bank model

Parameter	Meaning	Value	
π_H^1	BGP share of housing credit obtained from type-1 banks	0.576	
π_H^2	BGP share of housing credit obtained from type-2 banks	0.247	
	Share of non-housing firms with pref. $(0.95, 0.05, 0)$	0.336	
	Share of non-housing firms with pref. $(0, 0.95, 0.05)$	0.212	
	Share of non-housing firms with pref. $(0.05, 0, 0.95)$	0.297	
	Share of non-housing firms with pref. $(1/3, 1/3, 1/3)$	0.005	
Target	**Meaning**	**Model**	**Data**
E_{2000}^1	Share of housing in total credit, type-1 banks	56.6%	56.6%
E_{2000}^2	Share of housing in total credit, type-2 banks	44.4%	44.4%
E_{2000}^3	Share of housing in total credit, type-3 banks	30.9%	30.9%
$\overline{\mathrm{E}}_{f,2000}$	Average value of firm exposure	44.5%	45.8%
$\sigma\left(\mathrm{E}_{f,2000}\right)$	Standard deviation of firm exposure	9.7%	9.7%

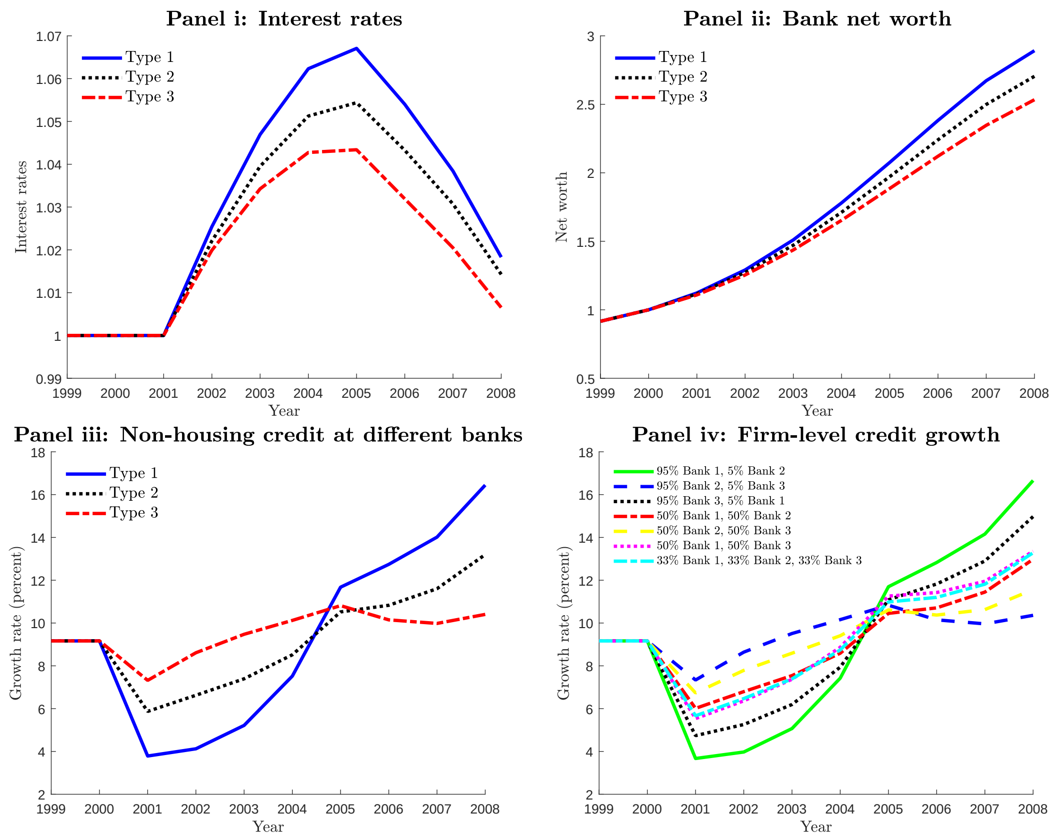
Given this structure, we first consider the predictions of the three-bank model when leaving all other parameters at their baseline values. Figure A.3 plots some key outcomes for this calibration. It shows that all predictions of the baseline model continue to hold: more exposed banks experience a greater initial increase in the interest rate, but also higher net worth accumulation. This triggers subsequent crowding-out and crowding-in effects at the loan and at the firm-level, illustrated in the two lower panels of the figure.

Table A.17 summarizes the quantitative predictions of the model with three bank types. The first column lists the baseline results. The second column instead lists the results for the three-bank model, leaving all parameter values except π_H^1, π_H^2 and $\boldsymbol{\theta}_N$ at their baseline values. It shows that the three-bank model also fits the data well, and that its aggregate implications are virtually identical to the two-bank model. Finally, the third column of Table A.17 shows results when we recalibrate the internal parameters g_A, ζ, ϕ and η_N in the three-bank model. Again, results remain very similar to the ones obtained with the two-bank model.

The slight dampening effect observed in Table A.17 suggests that bank heterogeneity is beneficial: non-housing credit falls less in an economy with more banks. This is a a bit more striking if we consider the results obtained in an economy with one bank (with an exposure equal to the aggregate value). In this single-bank economy, the crowding-out effect increases to -8.1% (full results are available on request). Indeed, with more banks, some non-housing firms (the ones with strong links to less exposed banks) are partly shielded from crowding-out. As the elasticity of substitution between non-housing firms is higher than 1, these shielded firms can make up partly for the lost output and credit of their peers linked to more exposed banks. However, the discussion in this section suggests that the dampening effect of bank heterogeneity is small.

[8] These assumptions imply that all non-housing firms are multibank firms, while in our baseline calibration, 89% of non-housing firms were single-bank firms. Nevertheless, as we show below, results are virtually unaffected, demonstrating that the high fraction of single-bank firms in the baseline calibration was not crucial for our results. Likewise, if we were to allow for single-bank firms in the model with three bank types, our results would not change either.

Figure A.3: The calibrated model with three types of banks



Notes: These figures illustrate some features of our calibrated model with three bank types. Calibrated parameters are listed in Table A.16 and in the main text.

Table A.17: Quantitative results: calibration with three banks

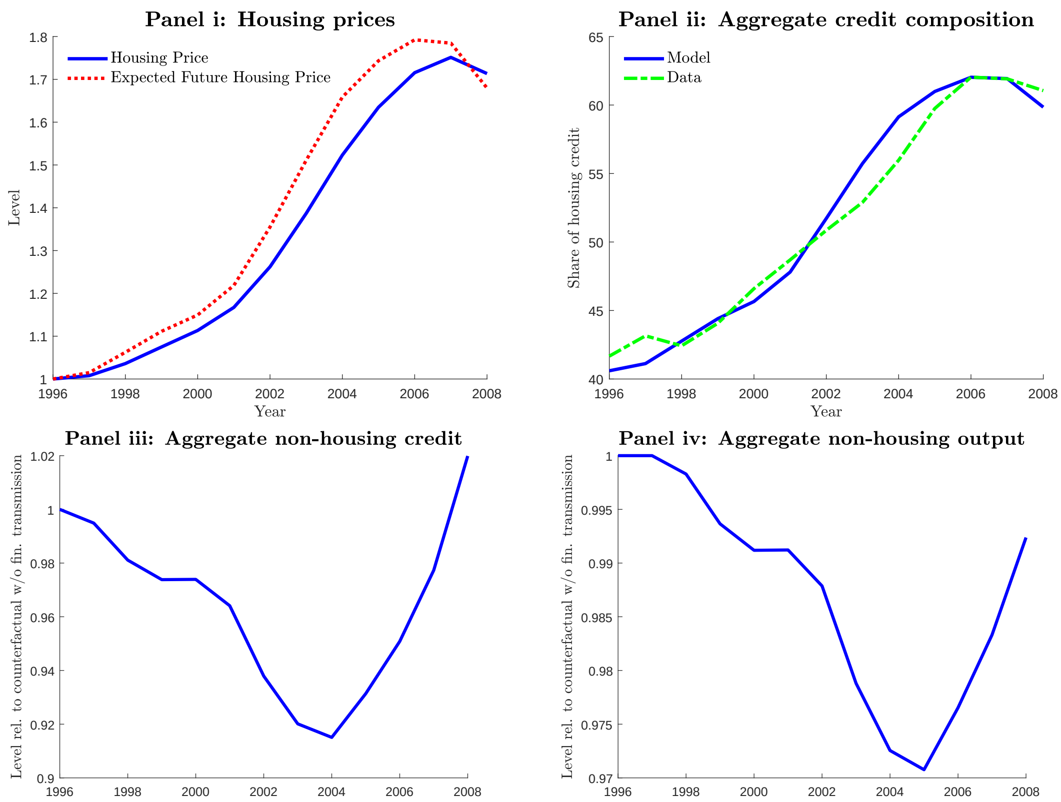
	Baseline	$B = 3$, baseline par.	$B = 3$, recalib.
Parameters			
ϕ	0.018	0.018	0.020
η_N	3.432	3.432	3.857
Targets (model)			
$\beta_{2001-2003}$	-2.85	-2.53	-2.79
$\beta_{2004-2007}$	3.89	3.65	3.98
$\gamma_{2001-2003}$	-2.66	-2.65	-2.60
$\gamma_{2004-2007}$	3.63	3.83	3.70
Level of non-housing credit rel. to counterfactual w/o financial transmission			
2004	-7.7%	-7.6%	-7.5%
2007	-2.0%	-2.0%	-1.9%
2008	$+1.8\%$	$+1.8\%$	$+1.8\%$

B.3.2 A longer housing boom

In our baseline calibration, we consider the time period 2000-2008, just as in our empirical analysis. However, as shown in Figures 1 and 2, housing prices and the housing share of aggregate credit already started to increase in the mid-1990s (even though the bulk of their increase came after 2000). Therefore, this section discusses a robustness check in which we consider the year 1995, and not the year 2000, as representing the pre-boom BGP.

In this robustness check, we use the time series of housing price changes between 1995 and 2008 (rather than the one between 2000 and 2008) as the shock hitting the economy. Furthermore, we reset the BGP relative productivity of housing to match the housing share in aggregate credit in 1995 (40.6%), and the scaling parameter ζ to match the increase in the housing share until 2007 (to 61.9%).[9] The remaining parameters are kept at their baseline calibration values. Figure A.4 illustrates the key results of this calibration. In particular, the third panel shows that the crowding-out effect still reaches its apex in 2004, lowering non-housing credit by 8.6% with respect to its level without financial transmission (rather than 7.7% in the baseline). In 2007, the shortfall is reduced to 2.2% (rather than 2.0% in the baseline), and in 2008, non-housing credit is 2.1% (rather than 1.8% in the baseline) higher than it would have been without financial transmission.

Figure A.4: Calibration with a long housing boom



Notes: These figures illustrate our model's predictions when we consider 1995 as the pre-boom BGP equilibrium and use the data series for housing price increases between 1995 and 2008. A_N and ζ are recalibrated as described in the text, all other parameters are set to their baseline values.

Thus, our estimates for the crowding-out effect of the boom until 2004 and for its net effect are very similar to our baseline estimates. Indeed, there are two offsetting effects: considering a housing price boom

[9]The implied parameter values are $A_N = 1.289$ and $\zeta = 0.715$.

starting in 1995 makes the overall shock larger (which, all else equal, increases the crowding-out effect), but it also lets the boom start with some years of relatively low housing price growth (which, all else equal, lowers the crowding-out effect, as banks accumulate some net worth before the years with the steepest price increases). The effect of a larger shock dominates, but our conclusions are not substantially altered.

B.3.3 Perfect foresight for housing prices

Our baseline calibration assumes that agents have rational expectations for housing price growth (and that housing price growth follows an AR(1) process). As there is - to the best of our knowledge - no systematic data on house price expectations in Spain during the housing boom, we cannot test these assumptions.[10]

To examine the robustness of our conclusions with respect to different assumptions on expectation formation, we assume in this section that agents have perfect foresight with respect to future housing prices. Note that in this case, we do not need to make any assumptions on the stochastic process generating the observed path of house prices. We recalibrate the internal parameters to match the same baseline targets, and keep all other parameters at their baseline values.

Table A.18: Quantitative results: perfect foresight

	Baseline (Rat. Expectations)	Perfect foresight
Parameters		
ϕ	0.018	0.040
η_N	3.432	3.258
Targets (model)		
$\beta_{2001-2003}$	-2.85	-2.21
$\beta_{2004-2007}$	3.89	5.23
$\gamma_{2001-2003}$	-2.66	-2.18
$\gamma_{2004-2007}$	3.63	5.15
Level of non-housing credit relative to counterfactual w/o financial transmission		
2003	-7.3%	-7.5%
2004	-7.7%	-6.1%
2007	-2.0%	$+1.8\%$
2008	$+1.8\%$	$+4.7\%$

Notes: The baseline (first column) corresponds to Table 11. In the second column, we assume that agents have perfect foresight for future housing prices, and recalibrate the parameters g_A, ζ, ϕ and η_N to match the baseline targets.

Table A.18 summarizes the results. It shows that with perfect foresight, we get a crowding-out effect of very similar magnitude than in the baseline calibration (but the trough is reached one year earlier, in 2003 rather than in 2004). However, at the end of the boom, there is a stronger crowding-in effect. This difference is due to the fact that with perfect foresight, agents anticipate a fall in housing prices at the very end of the boom, which lowers housing credit demand and boosts non-housing credit. Overall, however, results remain similar to the ones obtained with our baseline calibration.

B.3.4 Changes in bank leverage

In our baseline model, we assume that the leverage ratio of any bank is fixed over time. In reality, bank leverage increased during the housing boom, albeit modestly: the median leverage ratio of a bank in our

[10] García-Montalvo (2006) contains the only survey evidence that we are aware of, but it is limited to the year 2005 and to five cities.

sample increased from 11.56 in 2000 to 12.72 in 2007.[11] In this section, we examine whether this increase matters for our results. To do so, we make the parameter λ time-varying, and let it increase gradually from 11.56 in 2000 to 12.72 in 2007. This can be interpreted as Spanish banks being hit by a series of shocks that progressively loosened their financial constraints over the course of the boom.

Table A.19 illustrates the results for this robustness check. The second column shows our model's prediction with a time-varying leverage ratio, leaving all other parameters at their baseline calibration values. This shows that there is no direct interaction between the changes in the bank leverage ratio and the crowding-out and crowding-in effects: aggregate implications are virtually identical to the baseline.

Table A.19: Quantitative results: increase in leverage

	Baseline (fixed λ)	Increasing λ, baseline par.	Increasing λ, recalib.
Parameters			
ϕ	0.018	0.018	0.018
η_N	3.432	3.432	3.424
Targets (model)			
$\beta_{2001-2003}$	-2.85	-2.93	-2.85
$\beta_{2004-2007}$	3.89	4.04	3.92
$\gamma_{2001-2003}$	-2.66	-2.74	-2.66
$\gamma_{2004-2007}$	3.63	3.77	3.67
Level of non-housing credit relative to counterfactual w/o financial transmission			
2004	-7.7%	-7.7%	-7.7%
2007	-2.0%	-2.0%	-2.0%
2008	$+1.8\%$	$+1.8\%$	$+1.8\%$

Notes: The baseline (first column) corresponds to Table 11. Column (2) and (3) assume that λ increases at a constant rate from 11.56 in 2000 to 12.72 in 2007. In Column (2), all other parameters are at their baseline values, in Column (3), the internally calibrated parameters are recalibrated to match the baseline targets.

The third column of Table A.19 instead shows the results obtained when recalibrating the internal parameters g_A, ζ, ϕ and η_N for the model with increasing leverage. The main effect of this recalibration is to reduce the productivity growth rate g_A (as part of aggregate credit growth is now explained by the increase in bank leverage). However, this hardly affects our estimates for ϕ and η_N, or our aggregate conclusions.

B.3.5 Different elasticities of substitution across firms

In our baseline calibration, we set the elasticity of substitution among non-housing firms to $\varepsilon_N = 4$. In this section, we explore how results change for alternative values. Table A.20 summarizes the results. Columns (2) and (4) show our model's predictions when only changing the value of ε_N, keeping all other parameter values fixed. Columns (3) and (5), on the other hand, show the predictions when we recalibrate the internal parameters g_A, ζ, ϕ and η_N in order to again match our cross-sectional estimation results.

As shown in Column (2), all else equal, a lower value for ε_N leads to smaller divergence at the firm-level, and higher divergence at the bank-level. This is intuitive. As Equation (15) shows, ε_N is the elasticity of the relative credit of non-housing firms with respect to their relative funding costs. Thus, with a lower value of ε_N, the same differences in funding costs lead to smaller divergence in firm credit. As there is less substitution across firms, there is more substitution within firms. Indeed, substitution across firms dampens

[11]Note that this figure corresponds to book leverage. As most banks in our sample are not publicly traded, we do not have measures of market leverage for them. Begenau et al. (2019) show that in the United States, book and market leverage behaved in the same way during the 2000-2007 housing boom, both increasing very slightly.

the divergence of interest rates across banks (as firms linked to low-exposure banks increase their credit demand to gain market share from firms linked to high-exposure banks). Thus, with a lower value of ε_N, interest rates diverge more and firms substitute more between different banks. However, Column (2) also shows that on its own, this change in ε_N hardly affects our model's aggregate predictions.

This changes when we recalibrate the model in order to again fit our cross-sectional estimates more closely. As shown in Column (3), the recalibrated model manages to match again the firm-level divergence observed in the data by setting ϕ to a lower level. This implies that it takes longer for more exposed banks to accumulate net worth: they therefore diverge more from less exposed banks, and there is a greater divergence in firm funding costs. On its own, of course, this increases the model's loan-level predictions even more, and so the calibration also selects a lower elasticity of substitution across banks η_N. Overall, in this recalibrated model, the slower net worth accumulation implies a larger aggregate crowding-out effect, as shown in the last three rows of Column (3).

Increasing ε_N, as shown in Columns (4) and (5), has the exact opposite effect: all else equal, a higher elasticity of substitution between firms increases firm-level divergence, and so the calibration selects a higher speed of net worth accumulation to compensate for this and keep matching the same data targets. This faster net worth accumulation implies that the aggregate crowding-out effect is smaller.

Table A.20: Robustness: different elasticities of substitution ε_N

	Baseline ($\varepsilon_N = 4$)	$\varepsilon_N = 3$, base. par.	$\varepsilon_N = 3$, recal.	$\varepsilon_N = 5$, base. par.	$\varepsilon_N = 5$, recal.
	(1)	(2)	(3)	(4)	(5)
Parameters					
ϕ	0.018	0.018	0.001	0.018	0.034
η_N	3.432	3.432	2.672	3.432	4.265
Targets (model)					
$\beta_{2001-2003}$	-2.85	-2.93	-2.65	-2.65	-3.00
$\beta_{2004-2007}$	3.89	4.68	4.16	3.02	3.56
$\gamma_{2001-2003}$	-2.66	-2.05	-2.38	-3.09	-2.81
$\gamma_{2004-2007}$	3.63	3.28	3.74	3.53	3.34
Level of non-housing credit relative to counterfactual w/o financial transmission					
2004	-7.7%	-7.7%	-8.9%	-7.7%	-6.9%
2007	-2.0%	-2.0%	-2.7%	-2.0%	-1.6%
2008	$+1.8\%$	$+1.8\%$	$+1.7\%$	$+1.9\%$	$+1.8\%$

To sum up, Table A.20 shows that our results do depend on our assumption for the elasticity of substitution across non-housing firms, mainly because this assumption influences our estimate for the crucial parameter ϕ. However, the magnitude of our results does not change much for reasonable values of this elasticity.

References

Amiti, M. and D. E. Weinstein (2018). How Much Do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data. *Journal of Political Economy 126*(2), 525–587.

Basco, S. and D. Lopez-Rodriguez (2017). Credit Supply, Education and Mortgage Debt: The BNP Securitization Shock in Spain. *Mimeo.*

Begenau, J., S. Bigio, J. Majerovitz, and M. Vieyra (2019). Banks Adjust Slowly: Evidence and Lessons for Modeling. Research Papers 3672, Stanford University, Graduate School of Business.

Bentolila, S., M. Jansen, and G. Jiménez (2017). When Credit Dries Up: Job Losses in the Great Recession. *Journal of the European Economic Association 16*(3), 650–695.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2018). Housing Price Booms and Crowding-Out Effects in Bank Lending. *The Review of Financial Studies 31*(7), 2806–2853.

Chodorow-Reich, G. (2014). The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

García-Montalvo, J. (2006). Deconstruyendo la burbuja inmobiliaria: expectativas de revalorización y precio de la vivienda en España. *Papeles de Economía Española* (109).

Saiz, A. (2010). The Geographic Determinants of Housing Supply. *The Quarterly Journal of Economics 125*(3), 1253–1296.

Santos, T. (2017a). Antes del diluvio: The Spanish banking system in the first decade of the euro. In E. L. Glaeser, T. Santos, and E. G. Weyl (Eds.), *After the Flood: How the Great Recession Changed Economic Thought*, pp. 153 – 208. University of Chicago Press.

Santos, T. (2017b). El Diluvio: The Spanish Banking Crisis, 2008-2012. *Mimeo*.