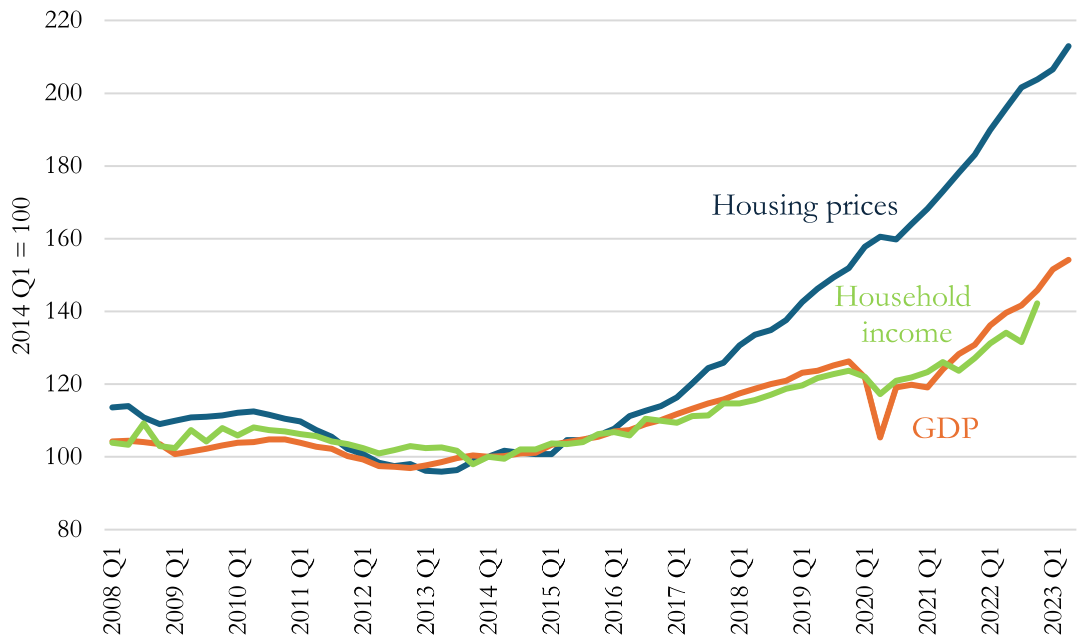
Appendix

Appendix A: Research Setting – Housing prices and affordability in Portugal

Figure A1 plots the evolution of housing prices in Portugal since 2008, in comparison with household income and GDP. The recovery from the economic and financial crisis has led to modest income growth which has failed to keep up with housing prices rising at a much faster pace. Even during the COVID-19 pandemic, prices showed little sign of being affected by the economic slowdown. This growing divergence between income and housing prices has resulted in a significant deterioration of housing affordability conditions for Portuguese households.

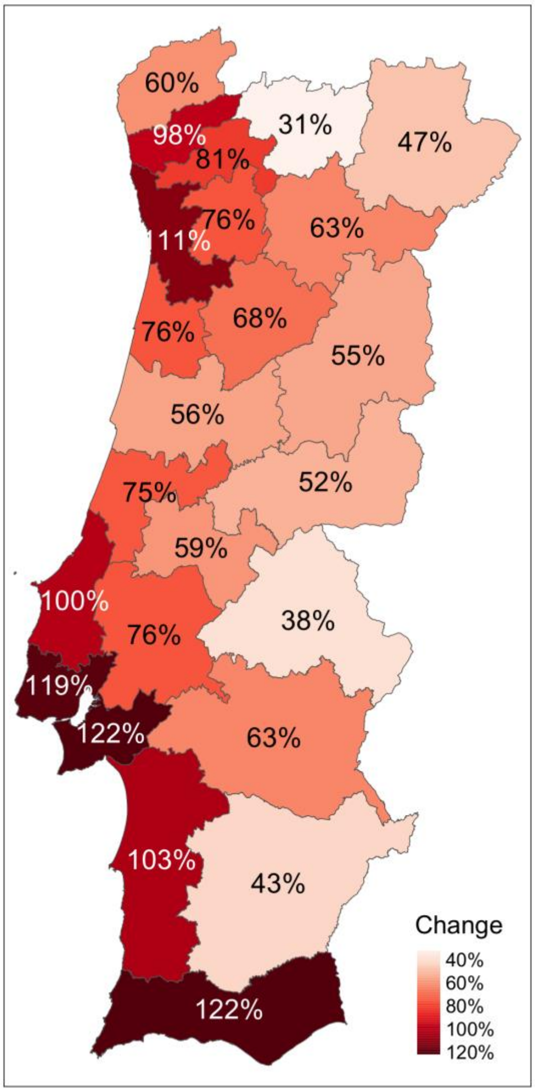
Figure A1: Housing prices, household income and GDP, 2008–2023 (nominal)[1]



This problem has been especially acute in a few areas of the country. Figure A2 shows the percentage increase in median house prices – measured by bank appraisals, which closely follow actual transaction prices – between 2014 and 2023 across all NUTS 3 regions of mainland Portugal.

[1] Authors' calculations, based on data from Portugal's National Statistics Office (INE).
INE (2023), House Price Index. INE, Lisbon. | INE (2023), Regional Economic Accounts. INE, Lisbon.

Figure A2: Change (%) in regional house prices (bank appraisals), 2014–2023[2]



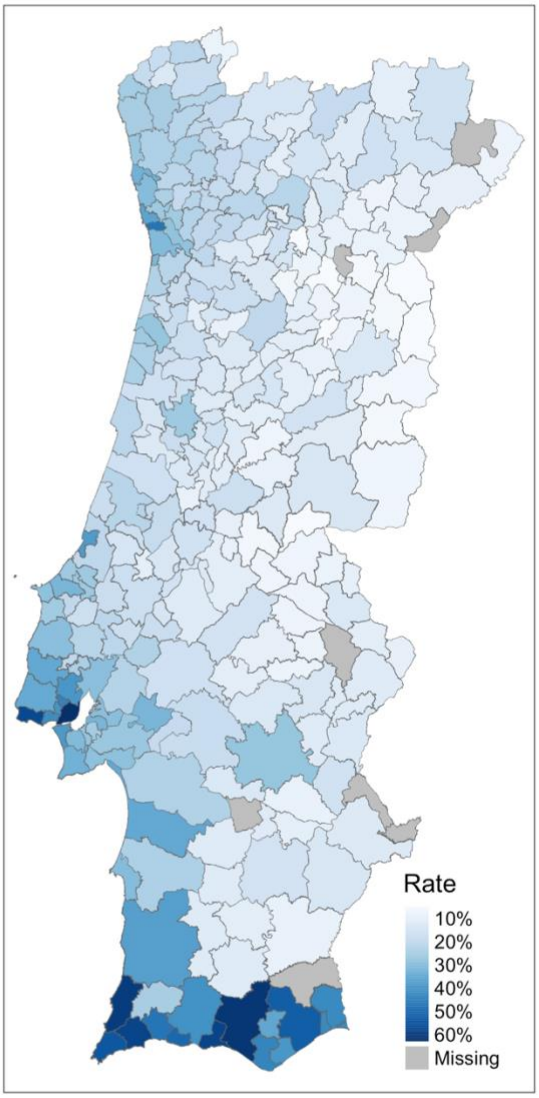
Prices have risen much more sharply in the two largest metropolitan areas, Lisbon and Porto, and in the southern region of Algarve than in the rest of the country. Moreover, as these urban centres are key economic engines offering an increasing share of employment opportunities (whether in tourism or more knowledge-intensive activities), they have become the main poles of attraction for migration flows, from both within the country (from poorer inland regions) and abroad.

High housing prices in the wealthiest and most productive areas of the country would not necessarily worsen housing affordability if firms were able to offer wages high enough to compensate greater cost of living. Hence, to assess current levels of housing affordability in Portugal, Figure A3 plots the share of net income that a median household in each municipality

[2] Authors´ calculations, based on data from Portugal´s National Statistics Office (INE).
INE (2023), National Survey of Housing Bank Appraisals. INE, Lisbon.

would need to allocate annually to purchase a 100 m^2 home, assuming they pay off the house regularly during a 40-year working life. The map illustrates how much worse affordability has gotten in the main metropolitan areas compared to the rest of the country. While in most municipalities this effort rate is below 20%, in nearly all municipalities in Algarve it reaches 40% or higher, 47% in Porto, and 63% in Lisbon. As this analysis excludes financing costs – and given that most households require a mortgage to purchase their homes – the actual financial effort required is even higher than reported here.

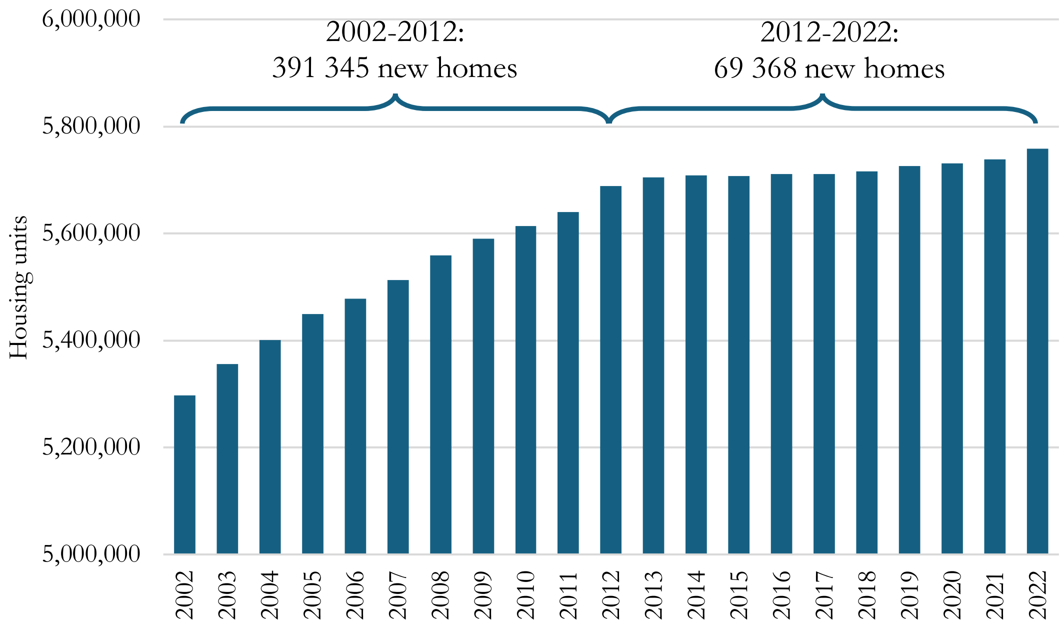
Figure A3: Housing affordability effort rates in municipalities, 2022[3]



[3]Authors' calculations, based on data from Portugal's National Statistics Office (INE).
INE (2023), Local House Price Statistics. INE, Lisbon.
INE (2023), Income Statistics at local level – Ministry of Finance - Tax and Customs Authority. INE, Lisbon.

Figure A4 shows the evolution of the housing stock (number of dwellings) in mainland Portugal over the past two decades, highlighting how the pace of new housing construction has notoriously slowed down after 2012.

Figure A4: Housing units, 2002–2022[4]



From an international perspective, Figure A5 shows that real housing prices have risen by 81.1% since 2015 as measured by the OECD's housing price index – the steepest rise among developed economies, compared to an OECD average of 32.1%. Also, the house price-to-income ratio (base year: 2015) reached 151.1 in 2024, the highest value across all OECD countries. The persistent deterioration of housing affordability in Portugal thus contrasts sharply with the relatively stable or improving trend observed in the OECD and Euro area averages since 2022 (see Figure A6).

[4] Authors' calculations, based on data from Portugal's National Statistics Office (INE).
INE (2023), Statistics on construction works completed. INE, Lisbon.

Figure A5: Real housing price index (base 2015), 2015-2024[5]

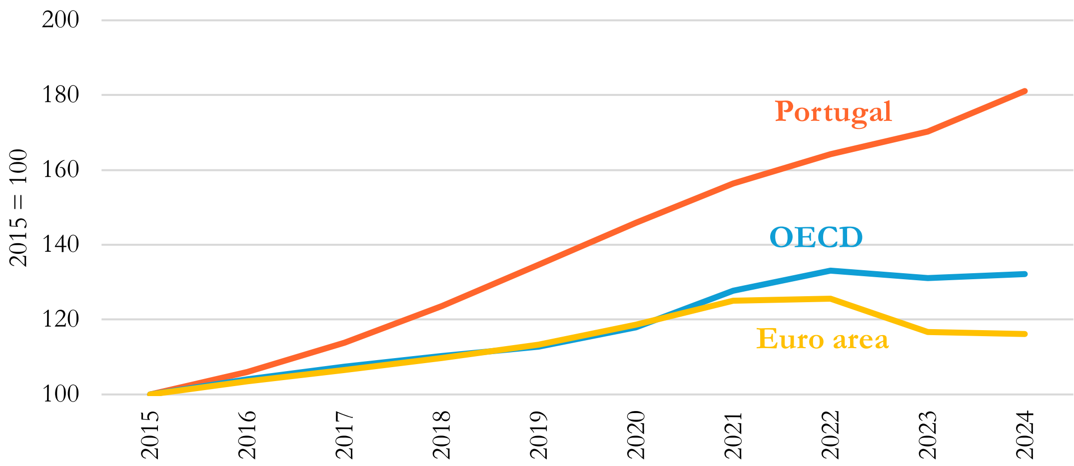
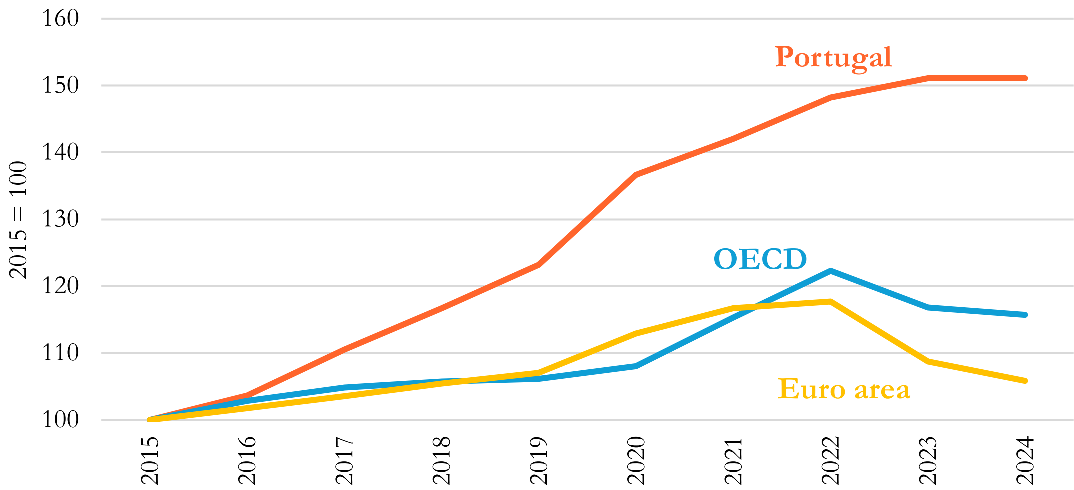


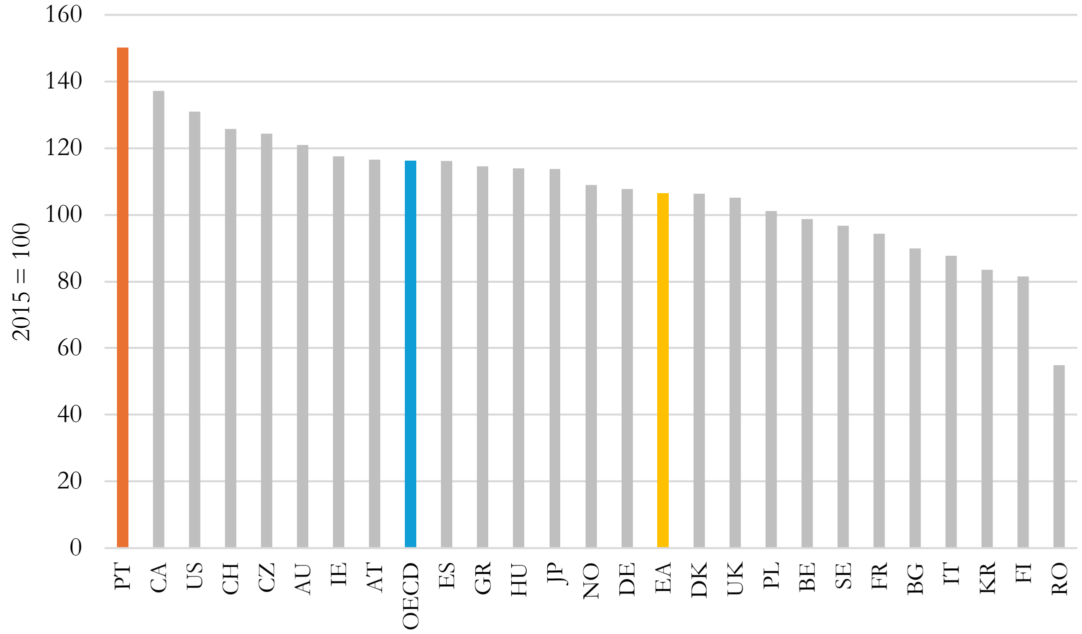
Figure A6: Housing price to income ratio (base 2015), 2015-2024[6]



The deterioration of housing affordability in Portugal is unmatched in Europe, with a rate more than twice that of the next worst-performing country, Switzerland (125.8). Comparable increases in the price-to-income ratio are found only in North America, where the ratio has risen by 37.1% in Canada and 30.9% in the United States (see Figure A7).

[5] Authors´ calculations, based on data from OECD; OECD (2025), Analytical house price indicators. OECD, Paris
[6] Authors´ calculations, based on data from OECD; OECD (2025), Analytical house price indicators. OECD, Paris

Figure A7: Housing price to income ratio (base 2015) in selected OECD countries, 2024[7]



[7] Authors´ calculations, based on data from OECD. OECD (2025), Analytical house price indicators. OECD, Paris

Appendix B: Robustness tests – spatial weight matrixes and missing values

Table B1 compares the coefficient estimates of the preferred house price model with those obtained by five alternative specifications of the spatial weight matrix $\mathbf{W}$. These include different functional forms of weights and distance thresholds. All matrices are row standardised. The model´s results remain generally consistent across these alternatives, except in column 5, where applying a 25km threshold appears to reduce much of the relevance of the spatial lag. Even so, the estimated total impact of housing supply remains similar across all columns, consistently around –0.5.

Table B2 considers a different weighting scheme, in which links between municipalities are based not on spatial distance but on observed commuting flows, as recorded in the 2021 census. The resulting model estimates are very similar.

Table B3 examines the effect of removing another 23 small municipalities from the sample – those with the lowest housing stock levels. We do so to demonstrate that the validity of the base model results should not be affected by the 23 small municipalities which were previously excluded due to missing values. Once again, the coefficients and total effects of housing supply remain broadly consistent.

Table B1: Estimates of house price model with alternative spatial distance matrices

	Base	**2**	**3**	**4**	**5**	**6**
W_{ij}^*	$\frac{1}{d_{ij}^2}$	$\frac{1}{\mathrm{d}_{ij}}$	$e^{-0.05\, d_{ij}}$	$e^{-0.1\, d_{ij}}$	$\frac{1}{d_{ij}^2}$	$\frac{1}{d_{ij}^2}$
Threshold	50 km	50 km	50 km	50 km	25 km	100 km
Constant	3.952 **	3.449 **	3.520 **	4.002 **	6.342 **	3.332 **
	(0.430)	(0.440)	(0.437)	(0.427)	(0.449)	(0.447)
$ln\ \mathrm{W}_i\mathrm{P}_t$	0.413 **	0.474 **	0.463 **	0.403 **	0.043 **	0.497 **
	(0.036)	(0.038)	(0.037)	(0.035)	(0.013)	(0.040)
$ln\ Y_{i,t}$	0.306 **	0.287 **	0.284 **	0.301 **	0.390 **	0.285 **
	(0.068)	(0.068)	(0.068)	(0.068)	(0.081)	(0.068)
$ln\ H_{i,t}$	-0.348 **	-0.320 **	-0.318 **	-0.344 **	-0.444 **	-0.320 **
	(0.070)	(0.070)	(0.070)	(0.070)	(0.084)	(0.070)
$ln\ F_{i,t}$	0.072 **	0.065 **	0.067 **	0.073 **	0.121 **	0.064 **
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.016)
$ln\ D_{i,t}$	0.031 *	0.031 *	0.032 *	0.032 *	0.039 *	0.033 *
	(0.015)	(0.015)	(0.015)	(0.015)	(0.018)	(0.015)
$ln\ T_{i,t}$	0.017 *	0.020 **	0.020 **	0.018 *	0.012	0.018 *
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$ln\ B_{i,t}$	0.060 **	0.055 **	0.055 **	0.060 **	0.075 **	0.057 **
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.014)
L_i	0.152 **	0.155 **	0.155 **	0.155 **	0.250 **	0.149 **
	(0.041)	(0.040)	(0.040)	(0.041)	(0.048)	(0.040)
K_i	0.065	0.083	0.083	0.065	-0.122 *	0.079
	(0.052)	(0.052)	(0.052)	(0.052)	(0.059)	(0.052)
τ_t						
2020	0.034 **	0.033 **	0.034 **	0.036 **	0.054 **	0.029 **
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2021	0.029 *	0.026 *	0.028 *	0.031 **	0.061 **	0.021
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
2022	0.043 **	0.035 *	0.038 **	0.047 **	0.102 **	0.028
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)
Total impact	-0.593 **	-0.609 **	-0.591 **	-0.575 **	-0.463 **	-0.636 **
of $ln\ H_{i,t}$	(0.117)	(0.129)	(0.126)	(0.114)	(0.087)	(0.136)
Observations	1020	1020	1020	1020	1020	1020
R^2	0.851	0.855	0.855	0.851	0.819	0.856
Log likelihood	551.71	560.49	559.56	551.04	503.64	560.23

Notes: ** statistical significance at 1%, * at 5%.

R^2 is the squared correlation of actual and fitted values.

Table B2: Estimates of house price model with commuting weight matrix

	Base	**2**
Constant	3.952 **	3.987 **
	(0.430)	(0.426)
ln W$_i$P$_t$	0.413 **	0.405 **
	(0.036)	(0.035)
$ln\ Y_{i,t}$	0.306 **	0.301 **
	(0.068)	(0.068)
$ln\ H_{i,t}$	-0.348 **	-0.345 **
	(0.070)	(0.070)
$ln\ F_{i,t}$	0.072 **	0.076 **
	(0.016)	(0.016)
$ln\ D_{i,t}$	0.031 *	0.036 *
	(0.015)	(0.015)
$ln\ T_{i,t}$	0.017 *	0.017 *
	(0.008)	(0.008)
$ln\ B_{i,t}$	0.060 **	0.063 **
	(0.014)	(0.014)
L_i	0.152 **	0.151 **
	(0.041)	(0.041)
K_i	0.065	0.057
	(0.052)	(0.051)
τ_t		
2020	0.034 **	0.038 **
	(0.011)	(0.011)
2021	0.029 *	0.034 **
	(0.012)	(0.012)
2022	0.043 **	0.048 **
	(0.015)	(0.015)
Total impact	-0.593 **	-0.580 **
of $ln\ H_{i,t}$	(0.117)	(0.114)
Observations	1020	1020
R^2	0.851	0.848
Log likelihood	551.71	552.80

Notes: ** statistical significance at 1%, * at 5%.
R^2 is the squared correlation of actual and fitted values.

Table B3: Estimates of house price model with further missing values

	Base	**2**
Constant	3.952 **	3.773 **
	(0.430)	(0.463)
ln W_iP_t	0.413 **	0.433 **
	(0.036)	(0.037)
ln $Y_{i,t}$	0.306 **	0.302 **
	(0.068)	(0.069)
ln $H_{i,t}$	-0.348 **	-0.337 **
	(0.070)	(0.072)
ln $F_{i,t}$	0.072 **	0.067 **
	(0.016)	(0.017)
ln $D_{i,t}$	0.031 *	0.033 *
	(0.015)	(0.015)
ln $T_{i,t}$	0.017 *	0.015 *
	(0.008)	(0.008)
ln $B_{i,t}$	0.060 **	0.060 **
	(0.014)	(0.014)
L_i	0.152 **	0.148 **
	(0.041)	(0.041)
K_i	0.065	0.076
	(0.052)	(0.052)
τ_t		
2020	0.034 **	0.031 **
	(0.011)	(0.010)
2021	0.029 *	0.026 *
	(0.012)	(0.011)
2022	0.043 **	0.040 **
	(0.015)	(0.015)
Total impact	-0.593 **	-0.593 **
of ln $H_{i,t}$	(0.117)	(0.123)
Observations	1020	928
R^2	0.851	0.853
Log likelihood	551.71	571.01

Notes: ** statistical significance at 1%, * at 5%.
R^2 is the squared correlation of actual and fitted values.

Appendix C: Robustness tests – instrumental variables

Table C1 relaxes the assumption that the level of the housing stock is exogenous to current prices through two different instrumental variable approaches – see Column 2 and Column 3. The results remain similar in both specifications (Column 3 indicates a slightly lower impact of housing supply on prices). Below we explain the rationale of using these two instrumental variable approaches as additional robustness checks.

Bartik-type variable (Column 2)

In Column 2, the number of housing units in each municipality is replaced with a Bartik-type instrument[8]. Here, the 'shift' is the annual number of units in each NUTS3 region[9], and the 'share' is each municipality's portion of the regional stock in 2011. The key assumption is that the local supply of housing and the housing characteristics are largely predetermined relatively to the contemporary housing demand volatility. It is assumed that the local exposure to fluctuations of housing supply depends on the initial exposure of each place to the housing supply, predetermined in a period where the current housing demand fluctuations were unforeseeable. The validity of this type of identification has been recently discussed under a more relaxed assumption that the aggregate shock is exogenous while the cross-sectional shares may be endogenous[10], in line with our approach.

Planning and regulation-related variable (Column 3)

In Column 3, housing supply is instrumented with a variable related to regulatory constraints in planning and new housing construction: the mean time of completion of new housing units (from issuing the licensing permit to the completion of the new unit), per square meter, as registered by municipalities each year, which we calculate using data requited to the Portuguese National Statistics Office (INE), which is available upon researchers' request[11].

The rationale of using this variable to perform a robustness test requires additional contextualization, notably as the success in the design of an instrumental variable depends critically on the institutional context of the housing regulatory framework being used to find exogenous

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[8] Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute

[9] European Nomenclature of Territorial Units for Statistical classification.

[10] Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of economic studies*, *89*(1), 181-213.

[11] Due to missing values in construction permit data, this specification was estimated with 8 fewer municipalities in relation to the main sample.

variation[12]. In Portugal, beyond national regulations, zoning and housing development regulation is largely based on municipal master plans (*Plano Diretor Municipal)*, which details the type of construction permitted in each municipality´s land. Their revision entails a prolonged political debate, detailed technical work and participatory processes usually surpassing a couple of years; furthermore, once in place, such plans should not be changed in the following three years, and should not last more than 10 years without revision. However, significant delays are common, reflecting intense bureaucratic work involved in adjusting master plans[13]. This implies that land use and zoning regulation tends to remain unchanged for more than 10 years, with the most recent significant changes taking place between 2014 and 2015, before the current rampant price appreciation in sub-national markets.

The instrumental variable used under this specification does not reflect directly these planning and regulatory zoning restrictions, but a mixture of those with the type of construction and the level of efficiency of municipal planning departments. Given i) the previously explained stability of regulatory frameworks, ii) the presence of cross-sectional differences in the efficiency of municipal planning departments, which are not likely to be short-term responsive to demand fluctuations, also for historical organizational reasons[14], and that iii) construction time is often dependent on the predetermined building stock, the type of land available and the agency of developers, it is unlikely that the cross-section dispersion of the chosen indicator follows demand fluctuations, specifically in a period of regulatory stability. Moreover, particularly in the case of housing permit issuance times, those can impose general costs on housing development which, as explained, are often not linked with the construction itself.

[12] Hilber, C. A., & Vermeulen, W. (2016). The impact of supply constraints on house prices in England. The Economic Journal, 126(591), 358-405.

[13] Pires, A. (2017). Breaking the ties with the master plan: spatial strategic plans in Portugal. In Albrechts, L, Alden, J., & Pires, A, *The changing institutional landscape of planning* (pp. 181-208). Routledge.

[14] Ferrão, J., & Campos, V. (2015). O Ordenamento do Território em Portugal: uma perspetiva genealógica [Territorial planning in Portugal: a genealogical perspective]. *Instituto de Ciências Sociais da Universidade de Lisboa. Lisboa.*

Table C1: Estimates of house price model under instrumented supply

	Base	**2**	**3**
Constant	3.952 **	4.049 **	3.413 **
	(0.430)	(0.429)	(0.419)
$ln\ \mathrm{W}_i\mathrm{P}_t$	0.413 **	0.411 **	0.422 **
	(0.036)	(0.036)	(0.036)
$ln\ Y_{i,t}$	0.306 **	0.324 **	0.202 **
	(0.068)	(0.067)	(0.044)
$ln\ H_{i,t}$	-0.348 **	-0.370 **	-0.220 **
	(0.070)	(0.069)	(0.044)
$ln\ F_{i,t}$	0.072 **	0.072 **	0.075 **
	(0.016)	(0.016)	(0.016)
$ln\ D_{i,t}$	0.031 *	0.029 *	0.041 **
	(0.015)	(0.015)	(0.014)
$ln\ T_{i,t}$	0.017 *	0.017 *	0.015 *
	(0.008)	(0.008)	(0.008)
$ln\ B_{i,t}$	0.060 **	0.063 **	0.052 **
	(0.014)	(0.014)	(0.013)
L_i	0.152 **	0.152 **	0.151 **
	(0.041)	(0.041)	(0.041)
K_i	0.065	0.063	0.075
	(0.052)	(0.052)	(0.051)
τ_t			
2020	0.034 **	0.034 **	0.033 **
	(0.011)	(0.011)	(0.010)
2021	0.029 *	0.027 *	0.035 **
	(0.012)	(0.012)	(0.011)
2022	0.043 **	0.041 **	0.056 **
	(0.015)	(0.015)	(0.013)
Total impact	-0.593 **	-0.627 **	-0.380 **
of $ln\ H_{i,t}$	(0.117)	(0.114)	(0.073)
Observations	1020	1020	980
R^2	0.851	0.852	0.851
Log likelihood	551.71	553.80	559.63

Notes: ** statistical significance at 1%, * at 5%.
R^2 is the squared correlation of actual and fitted values.

Appendix D – Spillover effects: estimation of direct, indirect and total impact

The inclusion of the autoregressive term means the regression coefficients of the spatial models are not directly interpretable as the marginal effect of each independent variable on prices. To see this, consider a reduced form of the spatial model in equation 4.9 in the main text, where $\mathbf{X_t}$ is the matrix of the right-hand side variables at time t, except the spatial lag, β are their respective coefficients, and ε_t the mean zero error terms:

$$ln\ \mathrm{P}_t = \rho\mathbf{W}\ ln\ \mathrm{P}_t + \mathbf{X_t}\beta + \varepsilon_t = (\mathbf{I} - \rho\mathbf{W})^{-1}(\mathbf{X_t}\beta + \varepsilon_t)\ , \qquad (Ap.1)$$

hence the expected values of the dependent variable come as:

$$E(ln\ \mathrm{P}_t) = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X_t}\beta\ . \qquad (Ap.2)$$

The marginal effect of the independent variable k is then calculated by taking the partial derivative of $E(ln\ \mathrm{P})$, which yields an N by N matrix $\mathbf{S_k}$:

$$\mathbf{S_k} = \frac{\partial E(ln\ \mathrm{P}_t)}{\partial \mathrm{X}_k} = (\mathbf{I} - \rho\mathbf{W})^{-1}\beta\ , \qquad (Ap.3)$$

which, expanded into an infinite series, can be written as:

$$\mathbf{S_k} = (\mathbf{I} - \rho\mathbf{W})^{-1}\beta = \sum_{n=0}^{\infty}(\rho\mathbf{W})^n\ \beta = (\mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \cdots)\beta\ . \qquad (Ap.4)$$

This elucidates the underlying dynamics of marginal effects in spatial models. A change in one location has immediate local effects to price, $\mathbf{I}\beta$, but also affects prices on surrounding locations, $\rho\mathbf{W}\beta$. By the same logic, these changes then cause further spillovers nearby, $\rho^2\mathbf{W}^2\beta$, and infinitely many subsequent spillovers, as the feedback effects percolate all spatial units. With $|\rho| < 1$, the spillovers become smaller and smaller and so the elements of matrix $\mathbf{S_k}$ converge to finite values. Each entry of the matrix, $s_{ij} = \frac{\partial E(ln\ P_{i,t})}{\partial X_{kj}}$, is the impact of a unit change in the variable X_k in location j on price in location i. Thus, not only are marginal effects tough to deduce from regression coefficients: they also differ across the N locations.

To facilitate a general interpretation of the marginal impact of each variable, three summary measures can be derived from each $\mathbf{S_k}$ matrix: average direct impact, average indirect impact and average total impact. Table D1 exhibits these impact measures and their respective standard errors as computed from the coefficient estimates of model 3 (see main text). Due to the log-log specification of the model, these impacts can be interpreted as elasticities.

Table D1: Impact estimates

	Direct	**Indirect**	**Total**
$ln\ Y_{i,t}$	0.314 **	0.207 **	0.521 **
	(0.070)	(0.050)	(0.115)
$ln\ H_{i,t}$	-0.358 **	-0.236 **	-0.593 **
	(0.072)	(0.052)	(0.117)
$ln\ F_{i,t}$	0.074 **	0.049 **	0.123 **
	(0.016)	(0.011)	(0.026)
$ln\ D_{i,t}$	0.032 *	0.021 *	0.053 **
	(0.015)	(0.010)	(0.025)
$ln\ T_{i,t}$	0.018 *	0.012 *	0.030 *
	(0.008)	(0.006)	(0.013)
$ln\ B_{i,t}$	0.062 **	0.041 **	0.103 **
	(0.014)	(0.010)	(0.023)
L_i	0.156 **	0.103 **	0.259 **
	(0.042)	(0.029)	(0.068)
K_i	0.067	0.044	0.111
	(0.054)	(0.038)	(0.091)

Note: ** statistical significance at 1%; * at 5%.

The diagonal terms of the matrix $\mathbf{S}_k$ express the marginal effect of a unit change in X_k in each location on the respective local price. The mean of these effects, given by $N^{-1}\ tr(\mathbf{S}_\mathbf{k})$, is defined as the average direct impact. Meanwhile, the off-diagonal elements of $\boldsymbol{S}_\mathbf{k}$ express the spillover effects of a unit change in X_k in one municipality to surrounding ones. The mean of these effects is defined as the average indirect impact. The results of Table D1 suggest therefore that a 1% increase in housing stock in one municipality results, on average, in a direct 0.358% decrease in housing prices in that municipality, and a decrease of 0.236% in housing prices in its surroundings. The average total impact, 0.593%, is the sum of both of these.

Since the total impact is essentially the mean of all elements in matrix $\mathbf{S}_\mathbf{k}$, $N^{-2}\sum_{i,j} s_{ij}$, this measure can also be interpreted as the mean of the row sums of the matrix, that is, the mean of the marginal effects resulting from a unit change in X_k across all locations. As such, Table D1 also allows us to predict, for example, that a 1% increase in housing stock in all municipalities would result in a 0.593% decrease in housing prices nationwide.

Appendix E – Alternative scenarios

The simulations of Scenarios 1, 2 and 6 (performed in the main article) assume supply expansion in the 2012-2022 decade. This would mean additional construction beginning at a time where Portugal was still under a financial and economic crisis. In Table E1 we consider instead scenarios where additional construction begins only after the economic turnaround, in 2015. In Scenario 1' we assume that construction in the 2015-2022 period would match the numbers of the 2001-2008 period preceding the Great Recession, and in Scenario 2' we assume that it would double those numbers. In practice, this would mean adding a similar number of units to the 2022 housing stock as in Scenarios 1 and 2 – roughly 300 and 700 thousand new units, respectively. The results of Scenarios 1' and 2' are therefore very similar, with price reductions of 3% and 7%. In the same vein, Scenario 6' simulates a policy mix, with the same supply expansion of Scenario 1, alongside the demand-side restrictions to foreign residents and tourist accommodations considered in Scenario 6; under these conditions, housing prices would decrease by 6%.

Table E1: Comparison of alternative simulated scenarios

Scenario	Price (€/m²)		Index	Effort rate	
Base: 2022	1 632		195.9	29.9%	
1': Maintain the pace of construction	1 579	–3.2%	189.5	29.0%	–1.0pp
2': Double the pace of construction	1 525	–6.6%	183.0	28.0%	–2.0pp
6': Policy mix	1 527	–6.4%	183.3	28.0%	–1.9pp

Notes: Price index base 2015 = 100; for reference, household income grew 40% in nominal terms in the 2015–2022 period (in all the scenarios, house prices would grow faster).

Appendix F – Foreign residents and homestay properties

Table F1: Evolution of foreign residents and homestay properties in Portugal[15]

		2015	2021
F	Foreign residents	374 741	764 349
B	Homestay properties (m^2)	4 785 625	21 316 641

Note: Figures refer to all municipalities of mainland Portugal

[15] INE (2023), Annual - Statistics Portugal, Foreign population with legal residence status. INE, Lisbon; Turismo de Portugal (2024), Homestay properties – open data. Turismo de Portugal, Lisbon.