

Immigration Narrative Sentiment and Home Prices

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Abstract

I use 1.38 million TV news transcripts to investigate the relationship between U.S. *home prices* and *immigration narrative sentiment*. One standard deviation orthogonalized shock to the sentiment Granger-causes a statistically significant and economically meaningful increase in home prices. The cumulative change is equivalent to about 25 percent of the Case Shiller Price Index average monthly change during the sample period. Moreover, the effect of a narrative sentiment shocks on home prices is permanent, which suggests that the immigration narrative contains fundamental information about home prices not captured by standard economic variables. Conversely, there is no evidence that home prices variation affects immigration narrative sentiment.

JEL classification: R31; G40; B55.

Keywords: Home prices; immigration, narrative economics; sentiment.

1 Introduction

Immigration is an important driving force for the U.S. economy. The effect of immigration on native labor has been studied by labor economists.¹ In more recent years, how immigration affects urban economics has received increasing attention from academia and policymakers alike. On the one hand, the inflow of migrants plausibly increases the demand for housing services and thus puts pressure on prices due to an upward-sloping supply curve. On the other hand, socioeconomic byproducts of immigration such as an outflow of natives and a downward pressure on wages could potentially negatively affect house valuation in the immigrants receiving areas.

How immigration dynamically relates to macroeconomic aggregates is difficult to ascertain. Detailed data about immigration flows are scarce and are mostly byproducts of the bureaucratic process associated with lawful immigration. Thus, they typically capture only incomplete aspects of the immigration phenomenon. For instance, the Migration Policy Institute (MPI) estimates that in 2019 there were about eleven million unauthorized immigrants among which over three million reside in homes that are owned, not rented.² Figure 1 shows the number of individuals obtaining permanent resident status during the period 2000 - 2020.

The effects of immigration are however related to the economic activity of all immigrants, whether legal or not, and natives' activity in response to

¹See e.g. [Borjas \(1995\)](#)

²Source: Migration Policy Institute (MPI) analysis of U.S. Census Bureau data from the pooled 2015-19 American Community Survey (ACS) and the 2008 Survey of Income and Program Participation (SIPP), weighted to 2019 unauthorized immigrant population estimates provided by Jennifer Van Hook of The Pennsylvania State University. <https://www.migrationpolicy.org/data/unauthorized-immigrant-population/state/US>

immigration. Moreover, it is plausible that, in addition to the direct economic effect of immigration, also the expectation of future immigrants inflow may have an economic impact. The existence, magnitude, and implications of these effects are empirical questions that deserve attention.

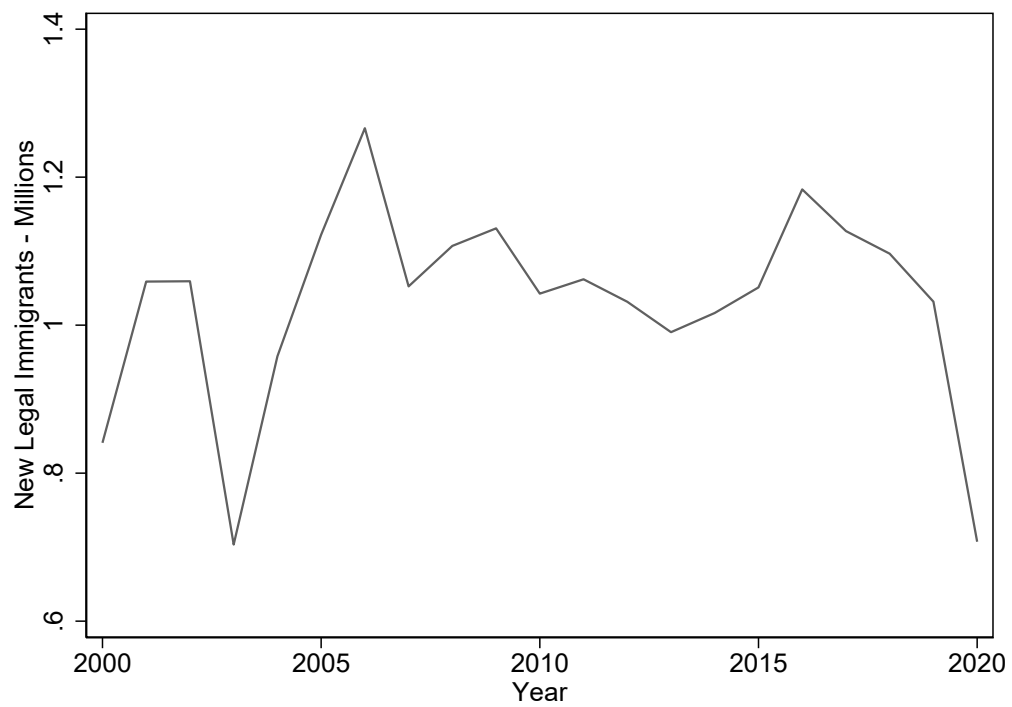


Figure 1: Persons Obtaining Lawful Permanent Resident Status. Annual. 2000–2020. Source: U.S. Department of Housing and Urban Development.

This paper contributes to the literature by investigating the relationship between *home prices* and the *immigration narrative sentiment* from TV news. Narrative economics is a new way of studying economic events pioneered by Robert Shiller. It investigates how economic activity is affected by the spread of stories.³ Narratives non only tell stories about the past and the present, but also contribute to shaping the future. Understanding how narratives relate to the economy can guide policy and help structure institutions.

I integrate Shiller’s narrative economics approach with Natural Language Processing (NLP) sentiment analysis.⁴ I hypothesize and test for the existence and magnitude of the relationship between home prices and immigration narrative sentiment. As a first step, I define a *narrative n-gram cluster*. The cluster is a set of n-grams chosen because they likely occur in a piece of TV news related to the immigration narrative.⁵ I then search the Internet Archive TV News section for each n-gram in the cluster. I retrieve about 1.38 million hits in total. I use a state-of-the-art natural language processing (NLP) algorithm to score each news passage and assign a quantitative measure of sentiment. The score captures the emotional tone and intensity of the text. Sentiment monthly time series are created by aggregating sentiment scores over time. The immigration sentiment series are finally used to model the fluctuation of home prices.

Panel Vector Auto Regression (PVAR) results show a significant association between home prices and immigration narrative. One orthogonalized

³Shiller (2017), and Shiller (2019).

⁴A similar approach is in Ackert and Mazzotta (2021), and Mazzotta (2022).

⁵An n-gram is a contiguous sequence of n items from a given sample of text or speech.

standard deviation shock to the immigration narrative sentiment Granger-causes an increase in the home prices of about 0.15. This cumulative change is economically meaningful and equivalent to about 25 percent of the Case Shiller Price Index average monthly change during the sample period. In addition, the shock to the narrative produces a long-lasting effect on home prices. This in turn indicates that some fundamental information about future home valuation is embedded in the immigration TV News narrative. However, shocks to home prices do not discernibly affect the immigration narrative sentiment.

The relationship between home prices and immigration narrative has not been studied. Therefore, this paper contributes to filling the gap in the urban economics literature and advances the field of narrative economics.

The remainder of this study is structured as follows. Section 2 reviews the literature. Section 3 illustrates the methodology. Section 4 presents the results. Section 5 discusses robustness and associated empirical tests. Section 6 discusses the results, and Section 7 offers some closing words.

2 Literature review

This section reviews home prices and immigration literature first, and narrative economics and sentiment next.

2.1 Immigration and Home Prices

Early immigration economics studies focus on foreign labor inflows and their effects on the economy.⁶ In a seminal paper, [Saiz \(2007\)](#) studies the relationship between immigration and home prices and identifies a causal association between immigration and rents in U.S. metropolitan areas. This work suggests that immigration generates additional demand for housing which in turn leads to increases in rents, and eventually increases in housing prices as well. A one percent increase in immigration in an urban area is associated with a one-half to one percent rent increase. The effect on home prices is about double as much. The rent increases occur largely soon after an immigration shock due to the short-term relatively inelastic housing supply. However, in the long term natives respond to immigration shocks by relocating away from areas with high migrant settlement density thus reducing pressure on prices.

Several later studies confirm the positive relationship between immigration and housing prices. [Akbari and Aydede \(2012\)](#) find a small but significant home price increase using panel data at census division levels. They conjecture that an outflow of the natives or an increased supply of housing due to expected higher demand in those areas may have determined the result. [Gonzalez and Ortega \(2013\)](#) document a causal link between immigration, labor force, and housing prices in Spain. Immigration determined an average 1.5 percent working-age population annual increase fueling an annual housing prices increase of about 2 percent and a 1.2–1.5 percent increase

⁶For surveys on the economics of immigration see [Kerr and Kerr \(2011\)](#), [Borjas \(2014\)](#), and [Card and Peri \(2016\)](#).

in housing units supply. Overall, immigration is found to be responsible for about fifty percent of the construction activity over the last ten years and about one-quarter of the price increase.

Mussa et al. (2017) find that immigration inflows into an urban area are associated with increases in house prices and rents within the same area but also in neighboring areas. The patterns observed are also consistent with native flight from immigrant-receiving areas. Gopy-Ramdhany and Seetanah (2022) study the dynamics of immigration and home price. They find that immigration significantly generally drives housing prices up in the short term, and in the long term in some areas. Monteduro et al. (2023) find that immigration positively and significantly affects house prices and rents. Sharpe (2019) argues that measurement errors cause upward bias in rent increases estimates and explicitly controls for immigrants' endogenous sorting. Once immigrants' attraction to areas with thriving economic conditions is taken into account, the effect of immigration on rents is attenuated. He also shows that natives' inflow effects on rent prices are *ceteris paribus* smaller.

In contrast with the results cited thus far, Sá (2014) find that immigration in the U.K. has a *negative* effect on house prices due to the relocation of the native population. Higher-income natives move out generating a negative income effect on housing demand and downward pressure on house prices. Peri and Sparber (2011) however dispute the existence of native displacement and point to modeling biases as the cause of inaccurate results.

Distinct from the flight argument typically found in the literature, Zhu et al. (2019) identify free renting associated with immigrant inflows as an additional cause of downward pressure on both housing quality and prices.

In summary, the empirical evidence preponderantly shows a positive relationship between immigration and home prices or rents. However, the opposite effects associated with natives’ relocation and measurement biases of various nature are hotly debated.

2.2 Sentiment

In the financial economics literature, sentiment is often defined as a discrepancy measure between rational and noise traders’ beliefs. [De Long et al. \(1990\)](#) suggest that sentiment generates risk that cannot be arbitrated away and therefore influences investment decisions. [Baker and Wurgler \(2007\)](#) maintain that “investors’ sentiment is an unjustified belief about investment risks and future cash flows.” [Brown and Cliff \(2004\)](#) relate sentiment to excessive pessimism or optimism. The common thread in these studies is that the rational investors’ limit to arbitrage combined with the irrational investor’s sentiment causes assets mispricing. In addition, [Shleifer and Vishny \(1997\)](#) maintain that bets against sentimental investors are risky and costly. Accordingly, rational agents are unwilling or unable to drive prices back to fundamentals.⁷

Natural Language Processing (NLP) and Artificial Intelligence (AI) have been recently used to extract sentiment from text for the purpose of economic analysis. [Soo \(2018\)](#) uses a word list to classify text from newspaper

⁷Several authors study how sentiment predicts financial performance. See e.g. [Brown and Cliff \(2004\)](#), [Chan \(2003\)](#), [Tetlock \(2007\)](#), [Uhl \(2014\)](#), [Heston and Sinha \(2017\)](#), [Chen et al. \(2022\)](#), and [Mazzotta \(2022\)](#). Yet another popular but different notion of sentiment based on surveys is used in the University of Michigan’s Consumer Sentiment index. See [UMCSENT \(2018\)](#). An exhaustive survey of the vast literature related to sentiment is outside the scope of this study. [Gupta et al. \(2020\)](#) and [Algaba et al. \(2020\)](#) provide up-to-date reviews.

articles as positive or negative. It finds that local housing media sentiment predicts future home prices. However, the news does not contain unobserved fundamental information. [Ackert and Mazzotta \(2021\)](#) find that the American homeownership narrative sentiment significantly explains home prices fluctuation unexplained by known economic factors.

3 Empirical Methods

A narrative is “a way of presenting or understanding a situation or series of events that reflects and promotes a particular point of view or set of values.”⁸ [Mazzotta \(2022\)](#) argues that “narrative and sentiment are intimately related” and contends that “a narrative drives economics events when it elicits sentiments that motivate individuals to take actions with economic consequences.” In this paper, the immigration narrative is the organizing principle that connects sentiment measures from TV news transcripts. The following section describes the empirical methods used to operationalize the approach.

3.1 Measurement of the Narrative

Studying narratives in a scientific manner is challenging, notes [Shiller \(2017\)](#). I hypothesize that a narrative can be characterized by a cluster of sub-topics and associated n-grams selected ex-ante. Natural Language Processing (NLP) algorithms can perform tasks such as image captioning, fake news detection, and sentiment scoring. Sentiment is defined as the *emotional tone*

⁸See e.g. Merriam-Webster dictionary.

behind a passage of text.⁹ Computational linguistics can be used to study the sentiment associated with the immigration narrative n-grams. I search the Internet Archive for the n-grams that characterize the immigration news, collect the transcripts, and use FLAIR, a state-of-the-art NLP algorithm, to classify each news passage.¹⁰ The algorithm can identify negative or positive tones and rate tones' intensity. A text passage receives a negative or positive sign and a score between zero and one. The sign describes the text negative or positive emotional tone. The score provides a measure of the emotion's intensity. Therefore, the sentiment in this paper is a measure of the intensity and polarity of the tone of a news passage that contains one of the n-gram in the cluster.

Note that the same facts underlying a piece of news can be narrated with tones that vary across anchors. For opinion shows the discord can be considerable.¹¹ Also, note that the sentiment score refers to the text passage classified by the NLP algorithm which may include no economic commentary.

Before using a sentiment classifier algorithm it is important to assess its accuracy. Note first that human classifiers do not always agree. For humans, 80-85 percent is the empirical best agreement baseline. The FLAIR algorithm accuracy is considered state-of-the-art because it approximates or exceeds human baseline scoring capabilities.¹² The immigration narrative sentiment monthly average time series from 15 n-grams are the inputs for

⁹An alternative and complementary approach is based on the Latent Dirichlet Allocation (LDA) of [Blei et al. \(2003\)](#). See e.g. [Li et al. \(2017\)](#), [Chen et al. \(2022\)](#), and [Mazzotta \(2022\)](#) for a discussion on the similarities and differences between the two approaches.

¹⁰See [Akbik et al. \(2018\)](#).

¹¹See e.g. [Bursztyn et al. \(2022\)](#).

¹²See e.g. [Wilson et al. \(2005\)](#), [Otter et al. \(2021\)](#), and [Li et al. \(2018\)](#).

the econometric analysis that follows.

3.2 Quantifying the Relationship

The previous subsection describes the methods to quantify the narrative. The next subsections introduce the methodology used to examine the relationship between home prices and immigration narrative home.

3.2.1 Home Prices and the Immigration Narrative

To ascertain the ability of the immigration narrative sentiment to predict home prices in conjunction with other well-known economic variables I estimate a vector autoregression (VAR) model.

Equation (1) represents the VAR model considered first.

$$\mathbf{Y}_t = \mathbf{c} + \sum_{l=1}^m \mathbf{A}_l \mathbf{Y}_{t-l} + \epsilon_t. \quad (1)$$

Equation (2) represents the vector of variables.

$$\mathbf{Y}_t = [HP_t \ PI_t \ NH_t \ W_t \ U_t \ P_t \ MR_t \ AS_t]', \quad (2)$$

$\mathbf{c}$ is a vector of constants, $\mathbf{A}_l$ is the coefficients' matrix for lag l , and ϵ_t is the error term. The VAR specification includes the six fundamental economic variables identified in [Case and Shiller \(2003\)](#). The home price variable HP_t is the U.S. National Home Price Index. The other variables are the personal income (PI_t), the housing starts (NH_t), employment (W_t), unemployment rate (U_t), change in population (P_t), and the mortgage rate (MR_t) from the Federal Reserve Bank of St. Louis. The narrative sentiment variable (AS_t) is

included as well. It is defined as the monthly weighted average score across the pre-selected 15 immigration n-grams, with weights being the relative frequency of each n-gram in the TV news during the reference month. The optimal lag structure from specification tests is $m = 2$.

All the variables in the model represented in equation (1) are treated as endogenous. Results discussed in detail in Section 5 indicate that none of the economic variables in (2) Granger-cause the average sentiment variable AS_t . Consequently, sentiment can be considered an exogenous variable for estimation purposes. Therefore, I consider a two-step approach next. First, I estimate the preliminary VAR model without sentiment represented in (3) and (4).

$$\mathbf{Y}_t = \mathbf{c} + \sum_{l=1}^m \mathbf{A}_l \mathbf{Y}_{t-l} + \epsilon_t, \quad (3)$$

with variables vector

$$\mathbf{Y}_t = [HP_t \ PI_t \ NH_t \ W_t \ U_t \ P_t \ MR_t]'. \quad (4)$$

This first step models the dynamic relationship among fundamental economic variables. It also produces residuals ϵ_t which capture the portion of each variable's fluctuation unexplained by the other economic indicators. In the second step, home price equation's residuals in model (3) are used in a Panel VAR with the n-gram immigration sentiment variable. The home price equation residual e_{HP_t} from the innovation vector ϵ_t in (3) allows investigating the dynamic relationship between home price purged of the effects of well-known economic factors, and the immigration narrative sentiment. The

following subsection describes the bi-variate Vector Auto Regression model.

3.2.2 Bi-variate Vector Auto Regression

I initially estimate a bi-variate VAR model between the innovations e_HP_t from the home price equation from (1) - (2) and the average narrative sentiment variable AS_t . This exercise is fruitless and results are not reported for brevity.

The Panel Vector Auto Regression (PVAR) of [Holtz-Eakin et al. \(1988\)](#) and [Abrigo and Love \(2016\)](#) model is estimated instead. The panel structure avoids information loss caused by the averaging across n-grams necessary to create the variable AS_t in the non-panel VAR. The PVAR model is estimated using the generalized method of moments and the [Arellano and Bover \(1995\)](#) forward orthogonal deviation transformation, which minimizes information loss.

A representation of the PVAR model is therefore:

$$\begin{aligned} P_{i,t} &= \gamma_{1i} + \sum_{j=1}^m \beta_{1j} P_{i,t-j} + \sum_{j=1}^m \delta_{1j} S_{i,t-j} + \epsilon_{1i,t} \\ S_{i,t} &= \gamma_{2i} + \sum_{j=1}^m \beta_{2j} P_{i,t-j} + \sum_{j=1}^m \delta_{2j} S_{i,t-j} + \epsilon_{2i,t} \end{aligned} \tag{5}$$

where $P_{i,t} = e_HP_t$ for all i 's are home price residuals described in the previous section. The sentiment variable $S_{i,t}$ is the monthly average sentiment scores for n-gram i , with $i = 1 \dots 15$, at time t , and m is the lag length. Coefficient of determination based tests suggest that the optimal lag structure is $m = 1$.

Equation (5) allows testing the hypothesis that immigration narrative sentiment explains home prices variation that the economic variables and their lags are unable to explain. This can be thought of as the genuine effect of the narrative on home prices.

4 Data

4.1 Textual Data from TV News

Text data for this study are originally from the Internet Archive which includes a repository of TV news transcripts.¹³ Processed data and sentiment scores are from Mazzotta (2022). Data and methodology are described in greater detail therein and only summarized here. The sample period spans October 2009 through December 2020. The corpus consists of 1.38 million TV news, with a count of 682 news on average each month.

4.2 Home Price and Economic Data

The home price and economic data are from the Federal Reserve Bank of Saint Louis. The selection of the measured of the fundamentals follows Case and Shiller (2003). The home price is the “S&P-Case-Shiller U.S. National Home Price Index”, (HP_t) . The other economic time series are: the personal income is the “Real Disposable Personal Income: Per Capita”, (PI_t) ; the new homes is the “New Privately-Owned Housing Units Started”, (NH_t) ; the employment is the “All Employees, Total Nonfarm”, (W_t) ; the unemployment

¹³<https://archive.org/>

is the “Unemployment Rate”, (U_t) ; the working population is the “Working Age Population: Aged 15-64: All Persons for the United States”, (P_t) ; the interest rate is the “30-Year Fixed Rate Mortgage Average in the United States”, (MR_t) .¹⁴ The first differences of all the variables are stationary and used in the empirical exercise.

¹⁴The series can be retrieved from the FRED database at <https://fred.stlouisfed.org/> using the following identifiers: CSUSHPINSA, A229RX0, HOUST, PAYEMS, UNRATE, LFWA64TTUSM647S, MORTGAGE30U

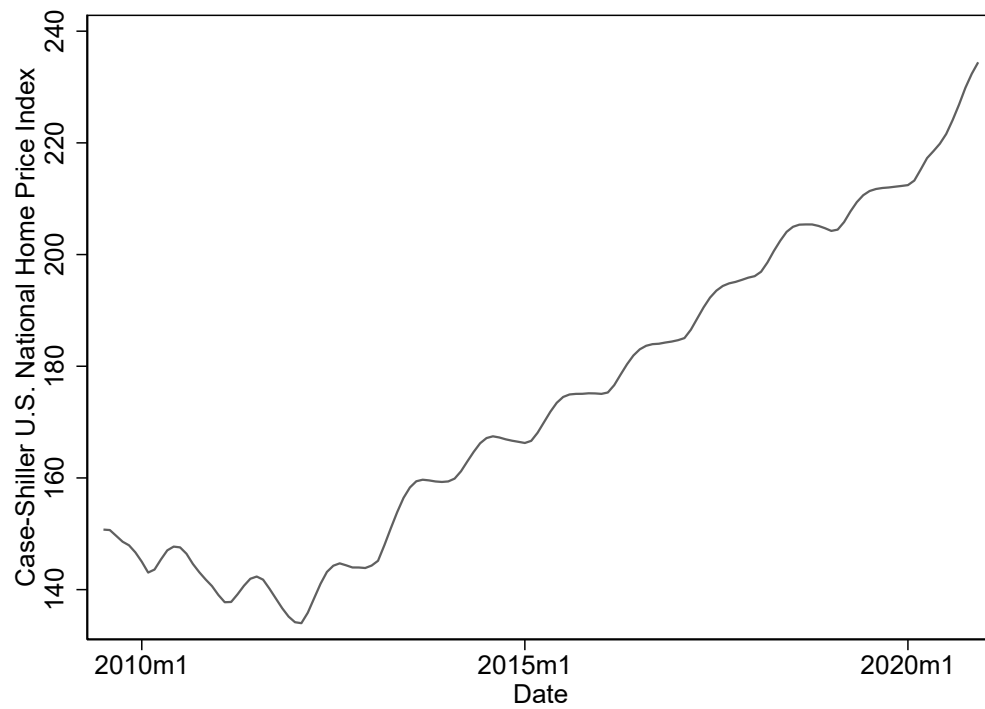


Figure 2: Case-Shiller Home Price Index, Monthly, October 2009 – December 2020. The index has been rebased and set equal to 100 in 2000.

4.3 N-gram Selection and Descriptives

Fifteen immigration n-grams occur in the TV news sufficiently frequently. The n-grams list, ordered from lowest to highest median sentiment, consists of *Illegal Immigrant*, *Asylum*, *Alien*, *Green Card*, *Undocumented*, *Legal Immigrant*, *Custom Enforcement*, *Refugee*, *Immigration Policies*, *Permanent Resident*, *Immigration Reform*, *Border Security*, *Migrant*, *Naturalization*, and *Immigrant Communities*. Some relatively common n-grams such as, *border enforcement*, *working visa*, or *citizenship requirements*, show coverage voids and yield time series with missing data.

Figure 3, 4, and 5 respectively show the monthly count, histogram, and sentiment time series for the 15 n-gram.

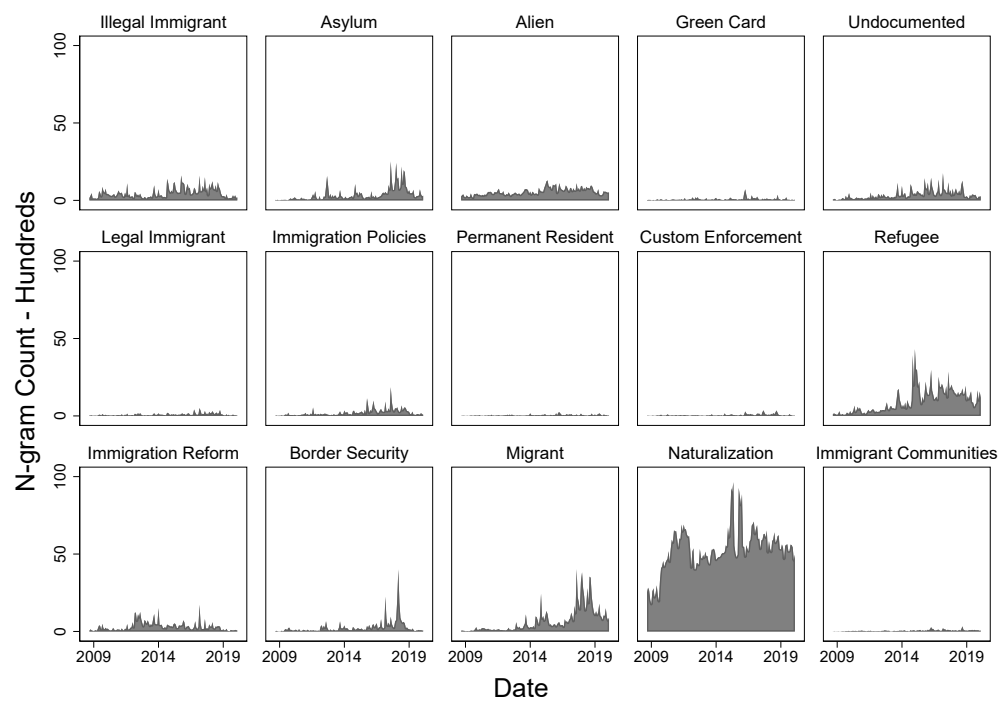


Figure 3: N-grams frequencies. Monthly. October 2009 – December 2020.

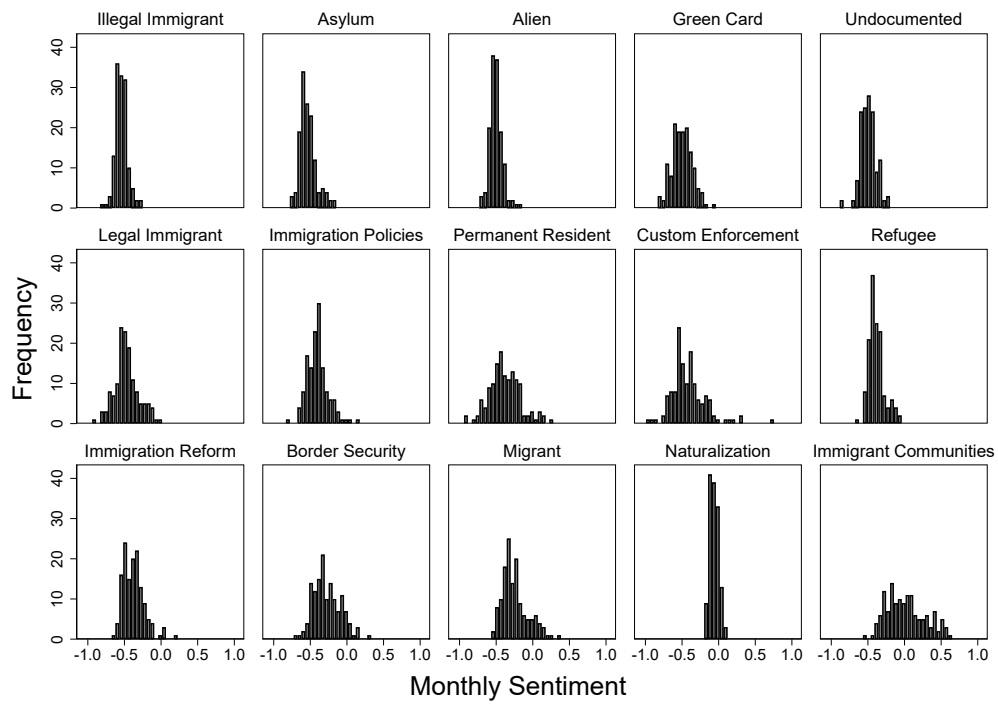


Figure 4: N-gram sentiment score histograms. Plot order is increasing in median sentiment score. Monthly. October 2009 – December 2020.

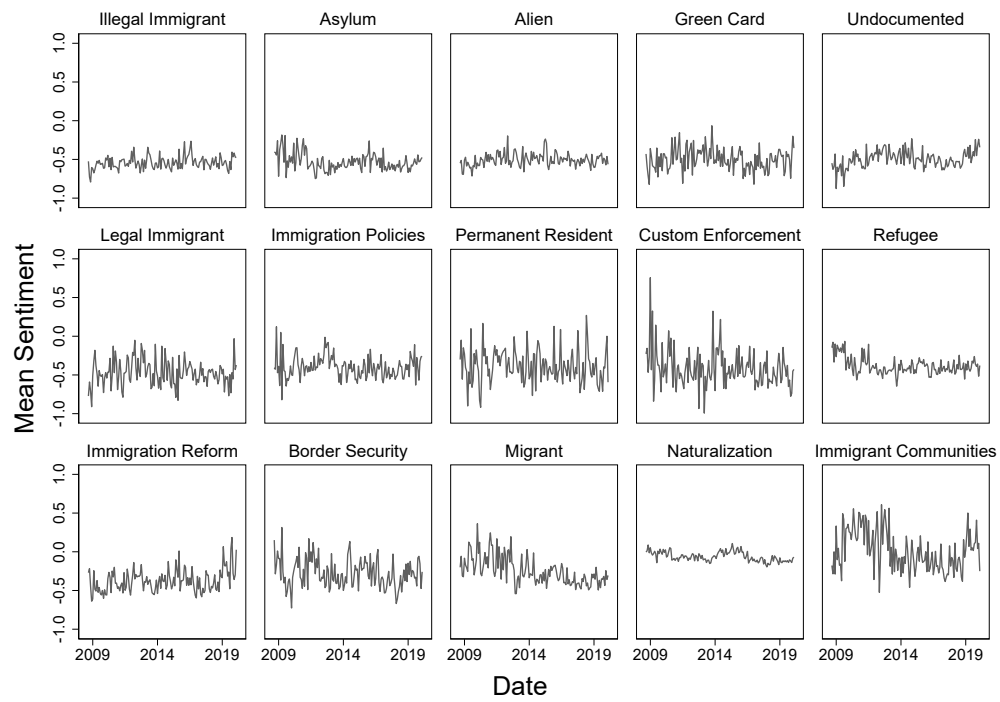


Figure 5: N-gram sentiment time series. Plot order is increasing in median sentiment score. Monthly. October 2009 – December 2020.

Tables 1 and 2 show n-grams frequency and sentiment summary statistics, respectively. Commentators often note the prevalence of negative news. [Trussler and Soroka \(2014\)](#) suggest that the newsmaking process is demand-driven and this type of stories are more numerous because the audience favors them.

Table 1: TV News summary statistics by N-grams. The sample period is October 2009 through December 2020, for a total of 138 months. The table reports the total frequency, the average number of news each month, and the median. Also reported are standard deviation, lowest and highest frequency.

N-gram	Frequency	Mean	Median	SD	Min	Max
All	1,394,052	673.46	182.50	1,384.42	2	9,646
Illegal Immigrant	69,454	503.29	416.50	339.29	92	1,610
Asylum	55,013	398.64	241.00	471.56	15	2,521
Alien	79,733	577.78	542.50	230.92	151	1,297
Green Card	11,266	81.64	57.00	88.56	7	719
Undocumented	54,032	391.54	294.50	324.80	20	1,758
Legal Immigrant	12,822	92.91	73.00	82.39	9	510
Custom Enforcement	8,289	60.07	39.00	61.55	3	363
Refugee	136,772	991.10	815.50	808.94	65	4,317
Immigration Policies	31,013	224.73	133.00	247.60	10	1,859
Permanent Resident	6,936	50.26	39.00	41.34	2	239
Immigration Reform	46,234	335.03	242.00	304.04	20	1,723
Border Security	37,706	273.23	134.00	463.65	7	4,004
Migrant	97,537	706.79	386.00	835.90	20	4,025
Naturalization	739,381	5,357.83	5,337.50	1,406.78	1,766	9,646
Immigrant Communities	7,864	56.99	45.00	48.00	2	333

Table 2: Sentiment from TV News summary statistics by N-grams. The sample period is October 2009 through December 2020, for a total of 138 months. The table reports the monthly mean, median, and standard deviation. It also reports the lowest and highest sentiment during the sample period. The sentiment measure is defined over the interval $[-1, 1]$.

N-gram	Mean	Median	SD	Minimum	Maximum
All	-0.37	-0.42	0.23	-0.99	0.76
Illegal Immigrant	-0.54	-0.55	0.08	-0.79	-0.26
Asylum	-0.53	-0.55	0.11	-0.75	-0.18
Alien	-0.50	-0.51	0.08	-0.71	-0.20
Green Card	-0.50	-0.50	0.14	-0.82	-0.06
Undocumented	-0.49	-0.50	0.11	-0.88	-0.23
Legal Immigrant	-0.47	-0.48	0.17	-0.91	-0.03
Custom Enforcement	-0.41	-0.45	0.24	-0.99	0.76
Refugee	-0.38	-0.41	0.11	-0.64	-0.07
Immigration Policies	-0.40	-0.41	0.15	-0.82	0.12
Permanent Resident	-0.38	-0.40	0.22	-0.92	0.27
Immigration Reform	-0.37	-0.38	0.15	-0.64	0.18
Border Security	-0.27	-0.31	0.19	-0.73	0.31
Migrant	-0.24	-0.29	0.18	-0.54	0.36
Naturalization	-0.06	-0.07	0.06	-0.20	0.11
Immigrant Communities	0.02	0.00	0.26	-0.52	0.61

5 Results

5.1 Vector Auto Regressions.

The summary results from the model in equation (1) are in Table 3. The VAR specification includes home price, the six fundamental economic variables identified in Case and Shiller (2004), and the weighted average sentiment described in Section 4. The home price variable HP_t , personal income (PI_t), the housing starts (NH_t), employment (W_t), unemployment rate (U_t), change in population (P_t), and the mortgage rate (MR_t). The narrative sentiment variable (AS_t) is included as well. The p-vals in Table 3 indicate that all the equations in the VAR system are highly significant. The values of the respective R^2 's suggest that predictability for all variables is sizable. Post-estimation tests confirm that the system is stable.

Table 3: Home Price Vector Autoregression with Average Immigration Sentiment

Equation	Parms	RMSE	R^2	χ^2	p-val
Home Price	17	0.41	0.894	1137.612	0.0000
Income	17	626.51	0.332	67.09	0.0000
New Homes	17	90.23	0.235	41.36	0.0005
Workers	17	1651.16	0.301	58.07	0.0000
Unemployment	17	0.86	0.285	53.83	0.0000
Population	17	221178	0.335	68.03	0.0000
Mortgage Rate	17	0.13	0.181	29.89	0.0186
Sentiment	17	0.01	0.215	36.96	0.0021

Table 4: VAR with Weighted Average Sentiment. Granger causality tests.

Equation	Excluded	χ^2	d.f.	p-val	Equation	Excluded	χ^2	d.f.	p-val
Home Price	Income	3.055	2	0.217	Unemployment	Home Price	2.374	2	0.305
Home Price	New Homes	1.172	2	0.557	Unemployment	Income	10.793	2	0.005
Home Price	Workers	5.996	2	0.050	Unemployment	New Homes	14.880	2	0.001
Home Price	Unemployment	1.599	2	0.450	Unemployment	Workers	2.700	2	0.259
Home Price	Population	13.387	2	0.001	Unemployment	Population	3.978	2	0.137
Home Price	Mortgage Rate	1.007	2	0.605	Unemployment	Mortgage Rate	0.426	2	0.808
Home Price	Sentiment	9.397	2	0.009	Unemployment	Sentiment	3.030	2	0.220
Home Price	ALL	41.312	14	0.000	Unemployment	ALL	50.301	14	0.000
Income	Home Price	2.792	2	0.248	Population	Home Price	4.390	2	0.111
Income	New Homes	13.752	2	0.001	Population	Income	9.116	2	0.010
Income	Workers	0.874	2	0.646	Population	New Homes	1.951	2	0.377
Income	Unemployment	1.557	2	0.459	Population	Workers	0.483	2	0.786
Income	Population	2.972	2	0.226	Population	Unemployment	2.415	2	0.299
Income	Mortgage Rate	0.326	2	0.850	Population	Mortgage Rate	4.236	2	0.120
Income	Sentiment	3.558	2	0.169	Population	Sentiment	0.909	2	0.635
Income	ALL	40.593	14	0.000	Population	ALL	49.809	14	0.000
New Homes	Home Price	0.432	2	0.806	Mortgage Rate	Home Price	0.381	2	0.826
New Homes	Income	12.669	2	0.002	Mortgage Rate	Income	0.882	2	0.643
New Homes	Workers	1.216	2	0.545	Mortgage Rate	New Homes	3.523	2	0.172
New Homes	Unemployment	2.484	2	0.289	Mortgage Rate	Workers	1.763	2	0.414
New Homes	Population	0.474	2	0.789	Mortgage Rate	Unemployment	2.814	2	0.245
New Homes	Mortgage Rate	0.365	2	0.833	Mortgage Rate	Population	0.599	2	0.741
New Homes	Sentiment	0.366	2	0.833	Mortgage Rate	Sentiment	3.070	2	0.215
New Homes	ALL	25.038	14	0.034	Mortgage Rate	ALL	10.420	14	0.731
Workers	Home Price	2.381	2	0.304	Sentiment	Home Price	0.117	2	0.943
Workers	Income	13.401	2	0.001	Sentiment	Income	4.195	2	0.123
Workers	New Homes	13.377	2	0.001	Sentiment	New Homes	2.710	2	0.258
Workers	Unemployment	2.911	2	0.233	Sentiment	Workers	0.656	2	0.720
Workers	Population	5.706	2	0.058	Sentiment	Unemployment	2.128	2	0.345
Workers	Mortgage Rate	1.235	2	0.539	Sentiment	Population	2.231	2	0.328
Workers	Sentiment	1.854	2	0.396	Sentiment	Mortgage Rate	0.003	2	0.998
Workers	ALL	51.085	14	0.000	Sentiment	ALL	12.643	14	0.555

Granger-causality test statistics are shown in Table 4. All the economic variables are jointly significant except the interest rate. These tests generally confirm known economic relationships among variables. Sentiment Granger-causes home prices. However, Granger-causation from sentiment to other economic variables is conspicuously absent. In other words, no economic indicator directly Granger-causes or is caused by the average immigration narrative sentiment. These results suggest that the predictability of home prices and the relationship between home prices and immigration narrative sentiment can be examined in separate stages. This is the object of the next section.

Figure (6) shows the impulse response function from the VAR with the average sentiment. The dynamics display a positive long-lasting impact from a shock on the sentiment to home prices. However, the estimates are not precise and the effect is not statistically significant at any time horizon.

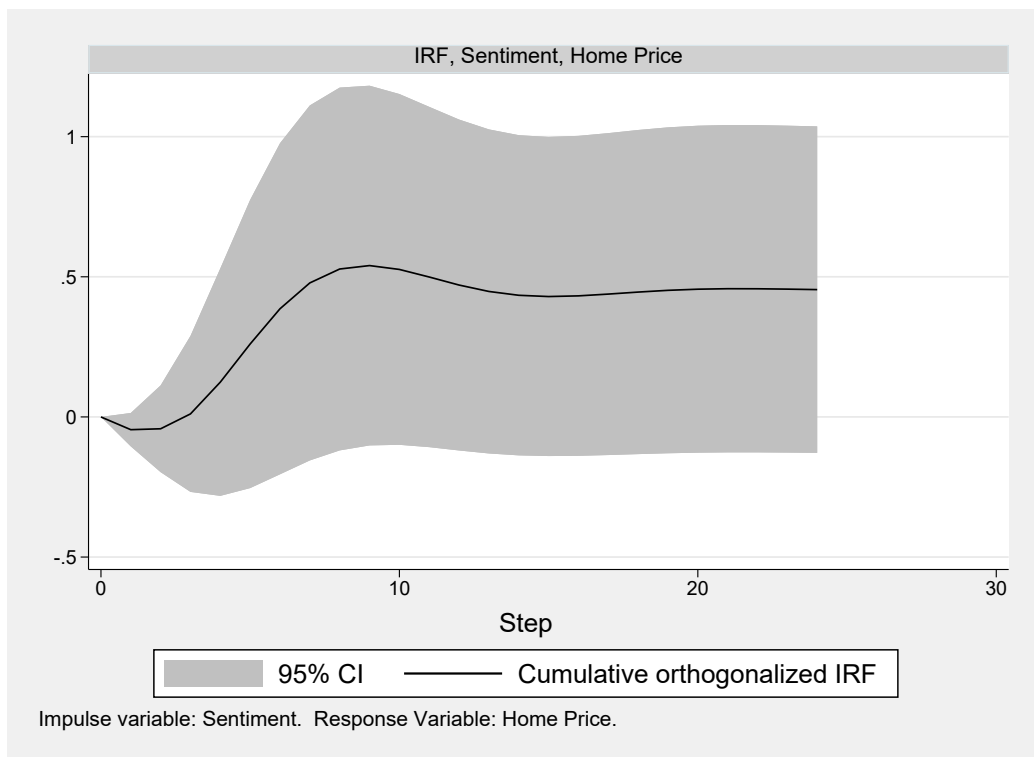


Figure 6: VAR Impulse response function.

Results from the home price predictability VAR model in equation (3) are in Table 5. The vector of variable is (4), and the sentiment variable AS_t is now excluded. The results mirror those in the model with the sentiment, except for a small R^2 decrease in the home price equation. Granger-causality tests results are very close to those reported in Table 4 and omitted to conserve space.

Table 5: Preliminary Home Price VAR with no Sentiment Variable

Equation	Parms	RMSE	R^2	χ^2	p-val
Home Price	15	0.42	0.887	1054.792	0.0000
Income	15	629.40	0.314	61.90	0.0000
New Homes	15	89.60	0.232	40.88	0.0002
Workers	15	1648.55	0.291	55.45	0.0000
Unemployment	15	0.86	0.269	49.68	0.0000
Population	15	220064	0.331	66.67	0.0000
Mortgage Rate	15	0.13	0.163	26.22	0.0242

The totality of the tests thus far suggests that a sizable portion of home prices is predictable, regardless of the inclusion of AS_t , the sentiment variable. It also suggests that averaging the sentiment over the cross-section of n-gram may cause a loss of information.

5.2 Panel Vector Auto Regressions.

Model (5) includes the residuals from home price index and individual n-grams narrative sentiment variables. The residuals are from VAR model (3), which does not include sentiment. The system is stable, and all the variables are stationary.

5.2.1 PVAR results.

Results from the Home Prices PVAR in equation (5) are reported in Table 6. The variable $P_{i,t}$ contains the innovations to home prices purged from the influence of other economic factors. $S_{i,t}$ is the sentiment monthly mean for n-gram i , with $i = 1...15$, on month t . The coefficient $\beta_{1,1}$ for the home prices is not statistically significant. This result obtains by construction as the predictability VAR in the previous stage purges the home price variable of its auto-regressive components, along with the influence of other lagged economic variables.

The coefficient on lag sentiment variable $\delta_{1,1}$ is positive and highly significant. Thus, immigration narrative sentiment drives home price variation net of other non-contemporaneous economic factors included in the predictability VAR model. The significance, magnitude, and sign of $\delta_{1,1}$ suggest that a positive shock to immigration sentiment drives a statistically significant,

and economically meaningful increase in the home price. This is the main contribution of the paper.

Table 6: Coefficients, standard errors, and p-val's for the Panel VAR. The system includes the Home Price Residual and the Immigration N-gram Sentiment. $P_{i,t}$ is the residual from the Home Price equation in Table 5. $S_{i,t}$ is N-gram i 's Sentiment score monthly mean. The system includes 15 panels for a total of 1,995 observations after lag adjustments.

$$P_{i,t} = \gamma_{1i} + \beta_{1,1}P_{i,t-1} + \delta_{1,1}S_{i,t-1} + \epsilon_{1i,t}$$

$$S_{i,t} = \gamma_{2i} + \beta_{2,1}P_{i,t-1} + \delta_{2,1}S_{i,t-1} + \epsilon_{2i,t}$$

	Lag Variables	Coefficient	SE	p-val
Home Price - $P_{i,t}$	$\beta_{1,1}$	0.012	0.028	0.662
	$\delta_{1,1}$	0.812	0.200	0.000
Sentiment - $S_{i,t}$	$\beta_{2,1}$	-0.003	0.010	0.771
	$\delta_{2,1}$	0.185	0.064	0.004
Panels		15	Obs.	1995

The Home Price lagged return coefficient $\beta_{2,1}$ in the Sentiment Equation is not significant. Thus home price does not affect immigration sentiment. $\delta_{2,1}$ sign and significance indicate that sentiment is positively auto correlated.

PVAR Granger-causality test results are in Table 7. The exclusion from the Home Price equation of the Sentiment variable is rejected at any conventional level. This confirms that Sentiment Granger-cause Home Price fluctuation. Conversely, the immigration narrative sentiment is not Granger-caused by home price variation. To summarize, immigration narrative sentiment explains a significant portion of the Home Price fluctuation that non-contemporaneous economic variables are unable to explain.

Table 7: PVAR. Granger-Causality Test.

Ho: The variable excluded does not Granger-cause Equation variable
 Ha: The variable excluded Granger-causes Equation variable
 D.f.= 1

Equation	Excluded	χ^2	p-val
Home Price	Sentiment	16.547	0.000
Sentiment	Home Price	0.085	0.771

PVAR model (5) Forecast Error Variance Decomposition is in Table 8. The table shows the amount of variation that Sentiment and the Home Price variables can explain of each other respectively. Sentiment drives up to about 8 percent of the home price variation. The contribution of Home Price on the Sentiment fluctuation is negligibly small.

Table 8: Home Price and Immigration Narrative Sentiment Forecast Error Variance Decomposition. The table shows the amount of variation that Sentiment and the Home Price variables can explain of each other respectively.

Forecast Horizon	Response Price		Response Sentiment	
	Price	Sentiment	Price	Sentiment
0	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0002	0.9998
2	0.9208	0.0792	0.0003	0.9997
3	0.9180	0.0820	0.0003	0.9997
4	0.9179	0.0821	0.0003	0.9997
5	0.9179	0.0821	0.0003	0.9997
6	0.9179	0.0821	0.0003	0.9997

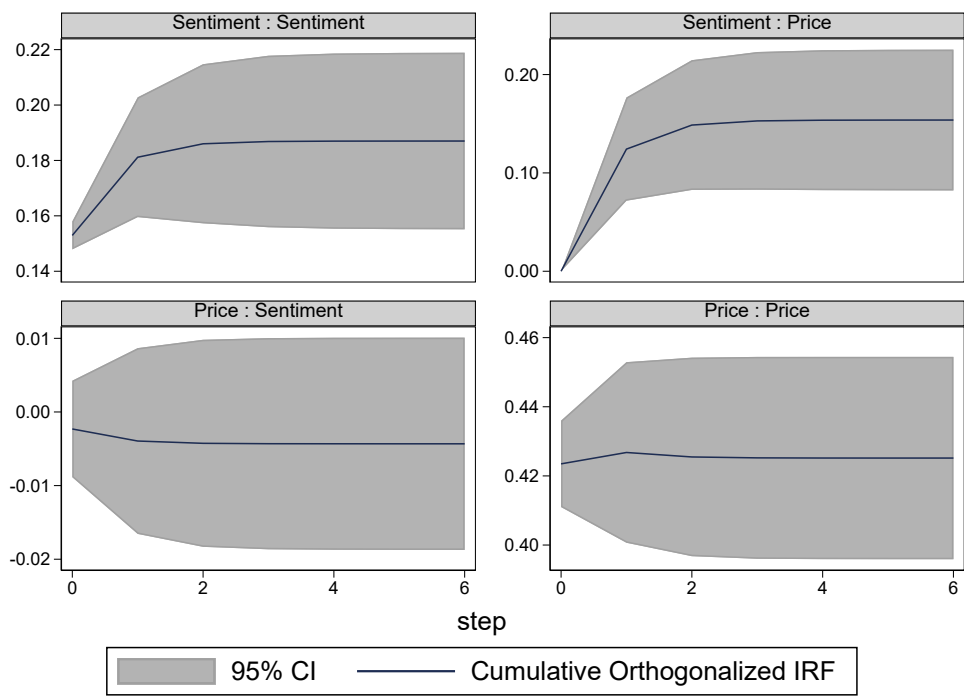


Figure 7: PVAR. Impulse response functions with 95 percent Confidence Intervals.

Figure 7 shows impulse response functions with 95 percent confidence intervals. The plots show how one standard deviation orthogonalized shock to one variable is expected to affect the other over the next six months. The top right figure shows how a shock to sentiment affects home prices. The effect is positive, significant, swift, and it does not revert over time. These results indicate that the sentiment from TV news immigration narrative affect home prices and, importantly, that the effect is permanent.

The results indicate that one standard deviation positive shock in the immigration news sentiment Granger-cause a cumulative increase of about 0.15 in the home prices as measured by the Case Shiller Price Index. The price index average monthly change being about 0.61, the increase is roughly equivalent to 25 percent of the change during the sample period.

In sum, the immigration narrative sentiment effect on home prices is economically meaningful and contains fundamental information about home prices that the market has not priced yet.

5.3 Robustness

As remarked, is difficult to pinpoint the contour of a narrative. To insure robustness several alternative specifications are therefore estimated. Note first that the selection of n-grams from the internet archive is limited. As a robustness test, 5 n-grams with a total of 46 missing observations spread out over the sample period were added to the 15 with the complete series considered in the previous section. The added n-grams are *customs and border protection*, *children of immigrant*, *path to citizenship*, *illegal entries*, and *immigration cases*. Since it is plausible that sentiment does not change

in absence of news, the missing months are filled by carrying forward non-missing observations. Standard diagnostics indicate that one lag is optimal and the augmented panel is stationary. Post estimation tests indicate that the system is stable.

The additional n-grams do not qualitatively change the results. Sentiment Granger-cause home price variation. The proportion of variance explained by the third forecasting period is however lower at to 3.4 percent, from 8.2 percent reported above.

Counting n-grams is a straightforward way to capture the spread of a narrative. To test to what extent n-gram monthly frequency may be informative, I estimate a bi-variate PVAR specification that includes the n-gram counts variable in place of the sentiment score. I also estimate a tri-variate PVAR specification which includes the count in addition to the home price and immigration narrative sentiment variable. Detailed results are not reported for brevity, but they confirm the results reported in the previous section. The count variable is statistically insignificant in all cases. The only variable that has a significant and long-lasting impact on Home prices is the Immigration Narrative Sentiment. It is plausible that counting n-grams without directly capturing emotional intensity may therefore yield a weaker test as compared to using sentiment.

The results in section 5 are therefore robust overall. The next section contextualizes the results in relation to previous work.

6 Discussion

The extant literature broadly identifies two main effects of immigration flows on home prices. The first is the increase in demand for housing services in immigrant-receiving areas. This drives prices up. The second is the native’s flight from immigrant-receiving areas in response to immigration flows, which works in the opposite direction and drives home prices down. The mechanics of these two opposing forces have been investigated both theoretically, and empirically. In most empirical studies the first effect prevails.¹⁵

The main result of this study is that a positive shock to the Immigration Narrative Sentiment Granger-cause a statistically significant and economically meaningful increase in home prices. Both, the methodology in this study, and the results are novel. A caveat is therefore that a direct comparison with results in the extant literature is not possible.

Nevertheless, if a positive shock in the Immigration TV news sentiment predicts immigration flows, then the results in this study plausibly align with the strand of literature that finds a positive relationship between immigration and home prices. It is evident that immigration flows and immigration narrative sentiment are entirely different constructs. Whether sentiment predicts immigration flows is an empirical question worth studying in its own right. The question is however not only beyond the scope of this study but also beyond what immigration data at hand permits. In fact, the short period and the annual frequency of immigration data are such that any statistical exercises attempt suffers from the lack of power.

¹⁵See e.g. [Saiz \(2007\)](#), [Gonzalez and Ortega \(2013\)](#), [Mussa et al. \(2017\)](#), [Gopy-Ramdhany and Seetanah \(2022\)](#), and [Monteduro et al. \(2023\)](#).

Irrespective of these data limitations, the correlation between changes in the numbers of Persons Obtaining Lawful Permanent Resident Status shown in Figure 1 and average annual sentiment from the immigration narrative is positive and equal to 0.049 contemporaneously and 0.274 at one lag. While far from amounting to conclusive evidence, these correlations support the conjecture that increases in the immigration narrative sentiment may foreshadow increases in immigrant inflows.

Note that studies point to the physical immigrants' flow as the starting point of the causal chain leading to home price increases (See e.g. [Saiz \(2007\)](#).) As noted, changes in population, housing starts, unemployment rate, and employment have been found to explain home prices. Concurrently, these same variables also reflect the economic effects caused by immigrants' inflows.

It is worth emphasizing that the effect of the Immigration Narrative Sentiment from TV News on home prices reported here is by construction measured net of such economic factors. This implies that the effects of actual immigration flows are not driving the results in this study. Therefore the effect on home prices reported here is genuinely driven by the Immigration Narrative Sentiment.

There are similarities between [Soo \(2018\)](#) and this study, but also two important differences. First, sentiment here does not depend on a dictionary.¹⁶ I use the n-gram clusters to screen the universe of TV news Archive for immigration narrative related News. Therefore, the sign of the sentiment from the NLP classifier is not affected by the n-gram cluster. Second,

¹⁶See [Loughran and McDonald \(2011\)](#).

Soo studies how the *housing market sentiment* from local newspapers affects home prices. Here the goal is to examine whether the immigration narrative sentiment relates to home price variation net of factors known to explain home prices.

This study also has some limitations. One limitation is that it does not attempt to identify the exact channels through which the immigration narrative affects home prices. Another limitation is that it does not attempt to quantitatively identify topics within the general immigration narrative and whether they may affect home prices in different ways. Yet another limitation is that this study does not account for potential biases in the TV News outlets and how they may affect the emotional tone of the news pieces. These themes are left for future research.

7 Closing Remarks

This study contributes to urban and narrative economics by characterizing the relationship between home prices and the immigration narrative. Thus far the relationship between home prices and immigration has been understudied. At the time of writing this paper, to my knowledge, no study examines the relationship between immigration narrative and home prices. This paper contributes to filling the gap.

I select a cluster of n-grams related to the immigration narrative and extract TV news transcripts from the Internet Archive. I use FLAIR, a state-of-the art Natural Language Processing (NLP) algorithm to assign a sentiment score to each passage. To empirically test whether and to what

extent home prices and the immigration narrative are related, I use Panel Vector Autoregression (PVAR) model. Home prices are positively related to immigration narrative sentiment from TV news. One standard deviation orthogonalized shock to the immigration narrative sentiment Granger-causes an increase in home prices of about 0.15. This effect is economically meaningful and approximately equal to 25 percent of the average monthly change in the Case Shiller Home Price Index during the sample period. Moreover, narrative sentiment shocks produce rapid and long-lasting effects on home prices. Conversely, home price shocks do not drive changes in the immigration narrative sentiment. Overall, these results suggest that the Immigration Narrative Sentiment contains fundamental information about home prices not reflected in standard economic variables and that the home market has not priced yet.

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