Fragmentation and Turnover Hold Back Labor Productivity in the Single-family Residential Construction Industry

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Abstract

Introduction

Construction labor productivity has declined over recent decades, despite gains in other sectors. Within residential construction, there has been a divergence in labor productivity between the single-family and multiple-family industries. Labor productivity has remained flat overall in the single-family industry while it increased in the multiple-family industry similar to the broader economy. This study uses these two related industries as a natural comparison for investigating differences in labor productivity trends.

Approach

I develop a simulation model for labor productivity in residential construction and calibrate it to historical data for both the multiple-family and single-family industries. The model includes construction pipeline, supply and demand regulated by price, labor force, and learning. I compare calibration results to investigate the divergence in labor productivity between the two industries. I also run scenarios that confirm those differences and test outcomes.

Results

The simulation model replicates historical data for both industries. Compared to the multiple-family industry, the single-family industry relies more on worker knowledge and has a higher level of employee turnover. Labor productivity in the single-family industry would increase with the lower fragmentation (more standardized projects) and the more stable workforce seen in the multiple-family industry.

Discussion

This study lays a foundation for modeling and investigating labor productivity in residential construction industries and beyond. The simulation model incorporates the labor force and its knowledge, replicates historical dynamics, and offers insights into labor productivity trends. Strategies for improving labor productivity in building homes could be especially useful for regions experiencing housing shortages.

Word count = 5477 words

1 Introduction

1.1 Motivation

Despite gains in other sectors, labor productivity in construction has declined. While overall productivity grew for the United States economy as a whole between 1970 to 2020, productivity in the construction sector dropped by an estimated 30 to 40 percent ([1], [2]). This trend is not unique to the US. Since 1995, construction labor productivity

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per hour worked in the European Union declined by over 15%. Meanwhile, all sectors together increased by over 39%, and manufacturing (another production-based sector) increased by over 97% during the same time period ([3]). The puzzle of why the construction sector has declined and not kept up with broader economic gains has long been a topic of study by economists and other researchers ([4], [5], [6], [7]).

Residential construction offers an avenue for exploring construction labor productivity among similar industries. The US Bureau of Labor Statistics (BLS) collects data related to productivity for two residential construction industries: multiple-family residential construction and single-family residential construction ([8], [9]). While these two industries are not exactly the same, they do share some important similarities. Their products are similar: they both build homes. They also both operate under similar regulatory environments that include building codes, zoning, and permitting. Furthermore, both industries also involve similar work tasks and occupations. Therefore, the multiple-family and single-family residential construction industries provide an opportunity for a natural comparison.

The BLS dataset ([8]) contains data from 1987 through 2024 and includes a labor productivity index. Rebasing this index so that 1987 = 100 and plotting it for the multiple-family and single-family residential construction industries shows a divergence in labor productivity over time. Figure 1 shows that while the multiple-family residential construction industry increased its labor productivity since 1987, the single-family industry has not.

Figure 1: Labor productivity index for the multiple-family and single-family residential construction industries.

Just as workers tend to improve with experience (learning by doing), one could expect the same from industries. According to learning and experience curves, performance and efficiency should improve as a function of cumulative production ([10], [11]). Yet, Figure 2 shows that labor productivity decreased as a function of output in the single-family residential construction industry, while increasing in the multiple-family industry. The learning curves in Figure 2 are plotted as $Y = aX^b$, and the learning rates are calculated as 2^b. Learning rates indicate the percent change in labor productivity when output doubles.

Meanwhile, in recent years metropolitan areas in the US and around the world have faced a housing crisis with prices increasing higher than many can afford. Building has not kept up with demand, creating a shortfall in housing supply ([12], [13], [14]). Recent estimates of the housing shortage in the United States are on the order of millions, ranging from 1.5 million homes to 5.5 million homes ([12], [15]).

Modeling the different patterns in labor productivity between the two residential construction industries can provide insights into why housing supply has not kept up with demand. This study investigates the decline in single-

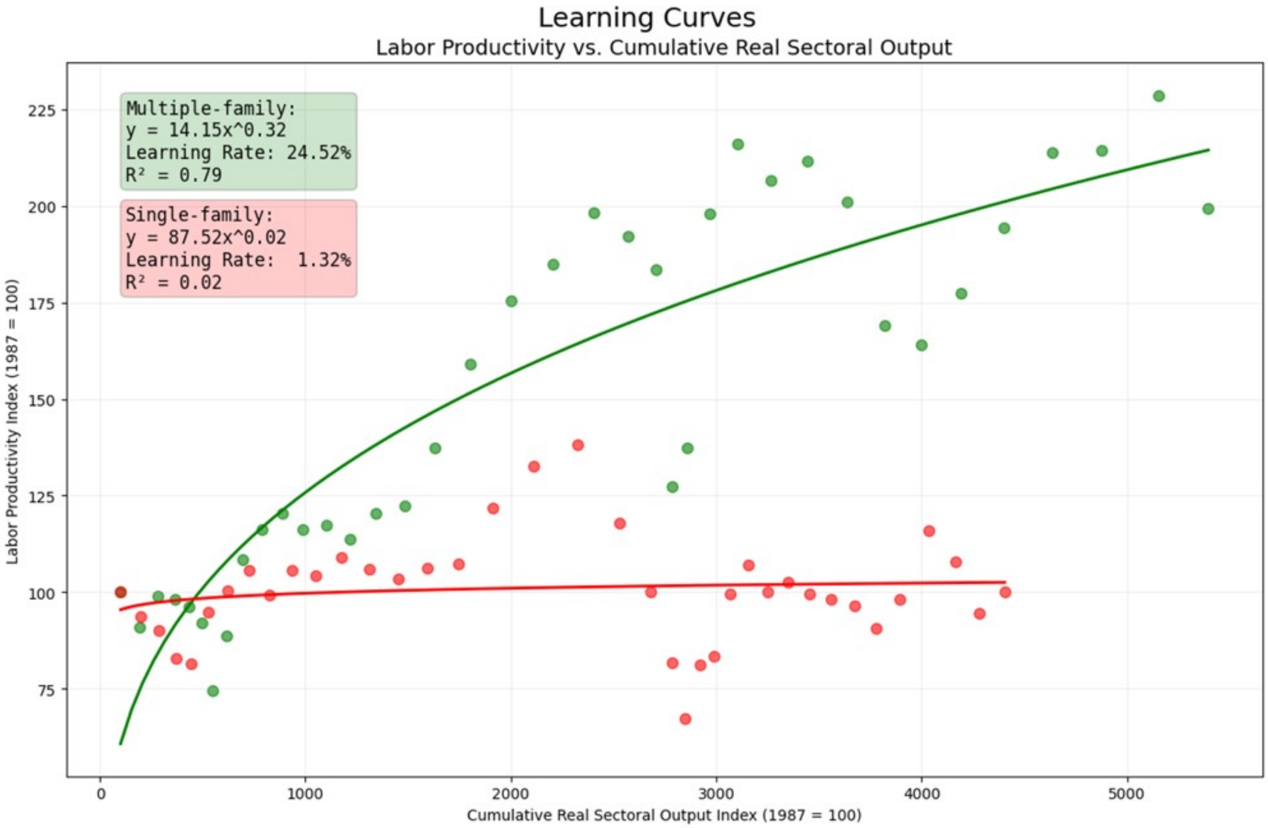


Figure 2: Learning by doing: labor productivity as a function of output.

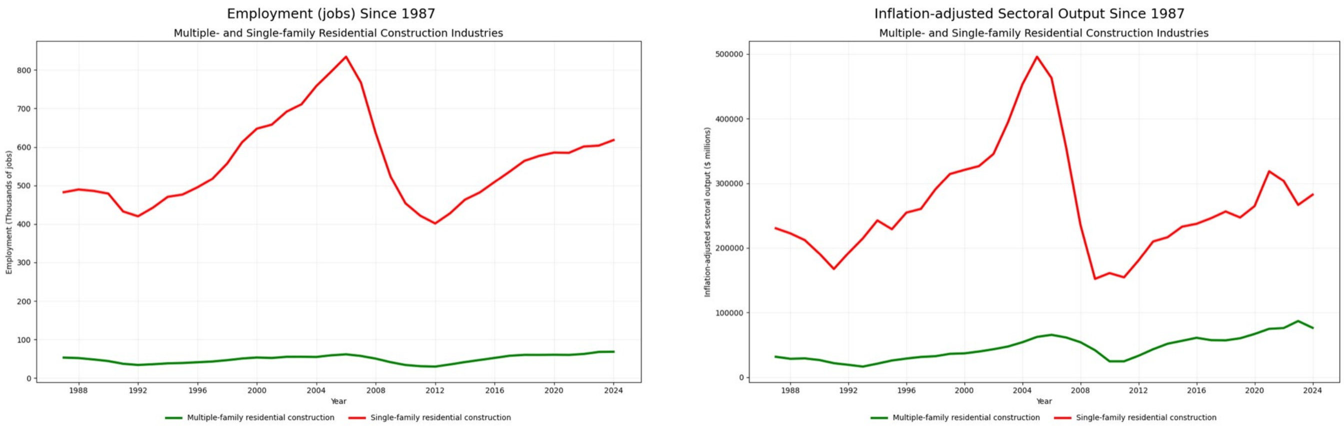
family labor productivity compared to the multiple-family industry. The resulting insights can inform strategies to improve productivity, build more homes efficiently, and ultimately help to alleviate housing shortages. Specifically, this study examines the roles that labor force, knowledge, and industry characteristics play in the divergence in labor productivity between the multiple-family and single-family residential construction industries.

1.2 Additional background

1.2.1 Industries

The BLS defines the multiple-family residential construction industry (NAICS 236116x) as consisting of contractors building multifamily residential structures such as apartments and condominiums; the single-family residential construction industry (NAICS 236115x) is defined as consisting of contractors primarily engaged in building single-family houses ([8]). These two industries are related and share some similarities (as noted above) like building homes and operating in similar environments. However, my analysis of BLS and US Census Bureau data ([8], [16]) also reveals some key distinctions. Most notably, the multiple-family residential construction industry in the US is much smaller than the single-family industry, both in number of employees and in real (inflation-adjusted) dollars of output. Figure 3 shows employment and output in the two industries over time.

There are also many more companies in the single-family industry, and the companies tend to be smaller. Figure 4 shows both the number of companies and the distribution of company size as measured by number of employees. In 2022, companies in the multiple-family residential construction industry had on average almost 14 employees compared to around just 4 employees in single-family companies. Moreover, 13% of workers in the multiple-family industry worked in large companies (those having 250 or more employees), compared to just 2% of single-family workers. On the other end of the spectrum, only 18% of multiple-family workers were employed by companies with fewer than 10 employees compared to more than 55% of workers in the single-family industry.



(a) Employment over time.

(b) Output over time in 1987 dollars.

Figure 3: The single-family residential construction industry is larger than the multiple-family industry.

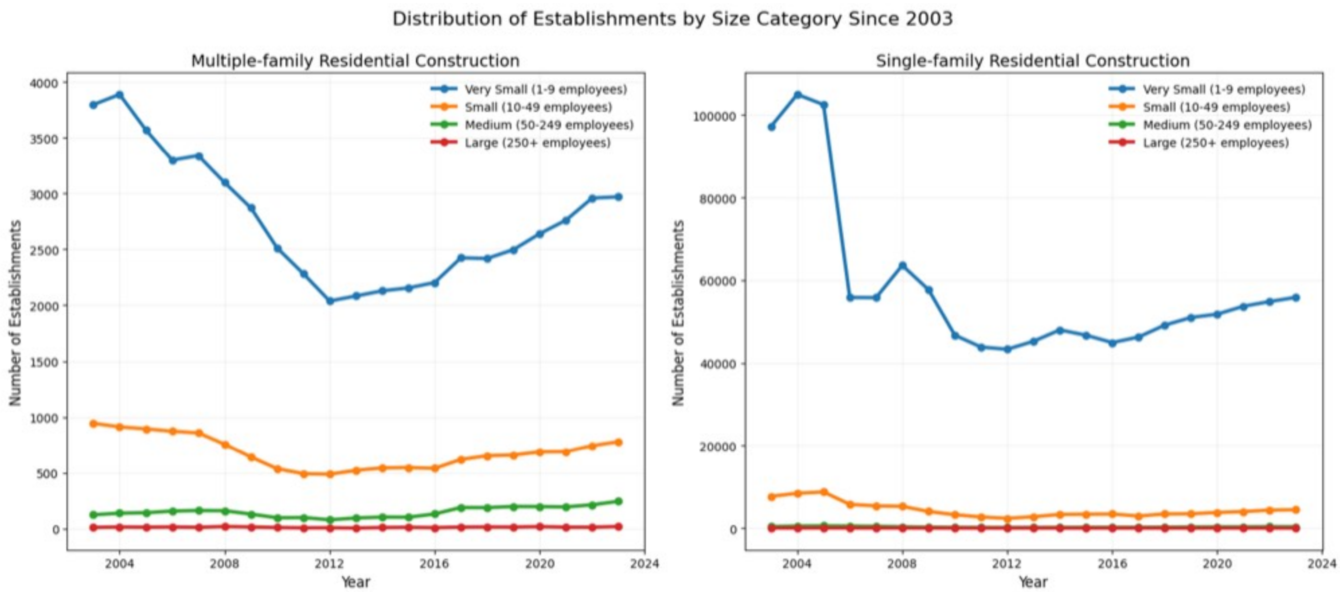


Figure 4: The single-family industry has more companies than the multiple-family industry, and companies in the single-family industry tend to be smaller.

These differences between the two industries lead to some interesting hypotheses regarding the divergence in labor productivity. For example, there is research indicating that higher fragmentation and smaller companies are related with lower construction productivity ([17]). In addition, the relative fragmentation of the single-family industry (many small companies) compared to the multiple-family industry could potentially help explain the lack of shared learning.

1.2.2 Dynamics of commodity production cycles

Dennis Meadows first introduced the dynamics of commodity production cycles in his 1970 book, extending the Cobweb Model from economics ([18]) and applying it to the US hog industry ([19]). The Cobweb Model could be thought of as a dynamic version of a supply and demand curve. As supply and demand adjust while seeking equilibrium over time with delays in information, production, and capacity, the oscillating movements in price draw what looks like a cobweb over the supply and demand curve. Meadows recognized these cycles as feedback loops and modeled them with system dynamics ([19]). John Sterman built upon Meadows' foundation with a chapter on commodity cycles in his seminal textbook, developing a generic commodity market model ([20]).

Housing construction is a production process and can be analyzed with a commodity cycle model. With housing, the suppliers are builders and the production is home construction, while demand comes from the population's housing needs. System dynamics has been utilized to study housing and real estate ([21], [22], [23], [24]) as well as other commodities such as cement ([25]). Sterman also names real estate as an example of an industry that exhibits strong cyclical dynamics ([20]).

1.2.3 Labor force and learning

The cycles in housing include the labor force and its knowledge and experience. The field of system dynamics has established structures for modeling various aspects of labor force, including turnover and experience ([20]). In general, when experienced workers leave and are replaced by less-experienced new hires, the average capability of the workforce declines. During expansions, the mass hiring of new and inexperienced workers can bring down average knowledge and experience, as well as productivity. Furthermore, when workers leave during recessions they take their accumulated knowledge and experience with them.

1.3 Paper outline

In this paper, I use a system dynamics approach to model and simulate the home construction pipeline, commodity cycle (demand, supply, production, and price), labor force, and learning for the multiple-family and single-family residential construction industries. I calibrate each industry to historical data. I compare respective parameter values to each other to understand the difference between the two industries, and hypothesize why their labor productivity trends have diverged. I also simulate different scenarios to observe their outcomes. This work is intended to reveal insights into the role that learning and labor force play in labor productivity in residential construction and other industries.

2 Methods

First, I plotted multiple variables over time by industry in order to identify and hone in on the puzzle, including investigating potential explanations. Then I developed a system dynamics model that included structure for construction, supply and demand, labor, and learning. Using historical data, I tested and calibrated this model structure. I then used this model to calibrate each industry separately to its own industry data. I analyzed the differences in resulting parameter values between the two industries to understand their labor productivity behavior in comparison to each other. I also conducted scenario tests informed by those industry differences.

2.1 Reference modes

I plotted variables over time by industry in order to better understand the two industries and their divergence in labor productivity. Table 1 lists these reference modes and the motivation behind plotting each one. Figures starting with "A" are located in the Appendix. Data for the reference modes were retrieved from the BLS ([8]), the Census Bureau ([16], [26]), and the Federal Reserve (FRED) ([27]). Any dollar values are real (i.e., inflation-adjusted). For easier visual analysis, I re-based indexes so that they would start at 100 in 1987, the beginning of the analysis time period.

Table 1: Reference modes plotted

Figure	Motivation	Variable(s)	Time span	Source
1	Visualize labor productivity divergence	Labor productivity index	1987–2024	BLS
2	Fit learning/experience curves	Labor productivity index and cumulative real sectoral output index	1987–2024	BLS
A1-a	Visualize labor productivity divergence, accounting for economic growth and year	Labor productivity index divided by GDP index	1987–2024	BLS, FRED
A1-b	Fit learning/experience curves, accounting for economic growth and year	Labor productivity to GDP ratio and cumulative real sectoral output	1987–2024	BLS, FRED
A1-c	Compare productivity at the worker level	Output per worker index	1987–2024	BLS
A1-d	Compare unit labor costs	Unit labor costs index	1987–2024	BLS
A2-a	Visualize employment trends over time	Employment index and number of jobs	1987–2024	BLS
A2-b	Compare hours worked trends over time	Hours worked index	1987–2024	BLS
A2-c	Compare trends in hourly compensation as a proxy for higher tech or skilled workers	Hourly compensation index	1987–2024	BLS
A2-d	Visualize labor compensation over time	Labor compensation index	1987–2024	BLS
A3-a	Compare output trends	Real sectoral output, index and dollars	1987–2024	BLS
A3-b	Compare the labor share (labor compensation as a proportion of output)	Ratio of labor compensation ($) to real sectoral output ($)	1987–2024	BLS
A3-c	Plot the gap between output and pay	Output per worker index minus compensation per worker index	1987–2024	BLS
A3-d	Compare trends in number of companies	Number of firms	2003–2022	Census
A4-a	Compare trends in company size	Average employees per firm/establishment	2003–2022	Census
A4-b	Compare industry consolidation	Average establishments per firm	2003–2022	Census
A4-c	Compare company sizes	Establishments by size category	2003–2022	Census
A5	Compare employee concentrations	Employment by establishment size	2003–2022	Census
A6	Compare output and hours per worker	Output per worker index and Hours per worker index	1987–2024	BLS

2.2 Calibration data

I used historical data to calibrate the models. Data for calibration were retrieved from the BLS ([8]), the Census Bureau American Housing Survey (AHS) ([28]), and the Federal Reserve (FRED) ([29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44]). Table 2 shows the variables and data sources I used. The AHS is conducted every two years, so data in the off years had to be interpolated. For data sourced from FRED, I summed multiple data series to arrive at the total for multiple-family units (for example, I summed the housing units in structures with 2–4 units and 5+ units). I adjusted price indices for inflation where necessary.

2.3 Model structure

I developed one model first and then used that same structure for the two industries. By sharing the same structure, the industries can be simulated separately, and any differences in important parameters can be compared. A subscript approach in Vensim that calibrates both models at the same time could have also been used; however, calibrating the two models separately was possible due to the availability of data by industry. Furthermore, the aggregate behavior of both models combined was also checked.

The final model consists of several major loops and sections of structure. First, I created the pipeline of construction as shown in Figure 5. Homes are started, spend some time under construction until they are completed and become part of the stock or inventory of homes, and then they are eventually removed (by demolition or natural disasters, for example).

Table 2: Data sources for calibration

Variable	**Model(s)**	**Data Source(s)**
Housing Starts	Multiple-family Single-family Total	FRED (HOUST2F, HOUST5F) FRED (HOUST1F) FRED (HOUST)
Housing Units Under Construction	Multiple-family Single-family Total	FRED (UNDCON24USA, UNDCON5MUSA) FRED (UNDCON1USA) FRED (UNDCONTSA)
Housing Completions	Multiple-family Single-family Total	FRED (COMPU24USA, COMPU5MUSA) FRED (COMPU1USA) FRED (COMPUTSA)
Housing Stock	All	Census AHS
Price	Multiple-family Single-family	FRED (BOGZ1FL075035403Q) FRED (CSUSHPINSA)
Labor Force	All	BLS
Population in housing units	All	Census AHS
Population in the United States	Total	FRED (B230RC0A052NBEA)
Average Household Size	All	Census AHS
Consumer Price Index (CPI)	All	FRED (CPIAUCSL)

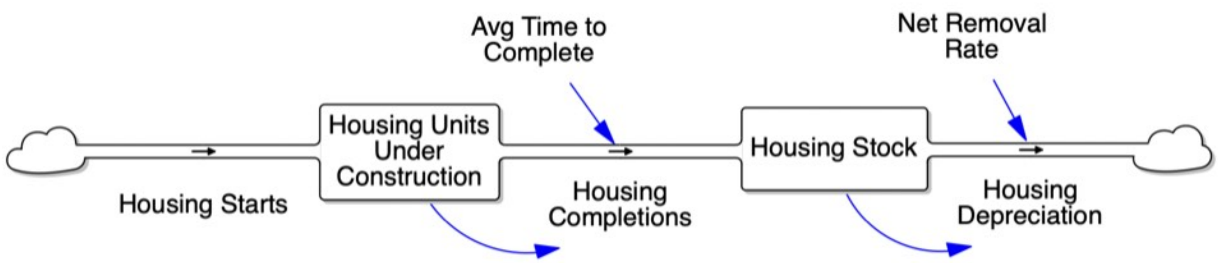


Figure 5: Construction pipeline.

The next piece of the model that I developed was based on the commodity cycle, which is essentially demand and supply regulated by price ([25]). Demand reflects the perspective of purchasers (i.e., home buyers), while supply reflects the perspective of producers (i.e., builders). Supply and demand (Figure 6) are connected to the construction pipeline. Demand is generated exogenously by population and average household size, which determine the potential need for homes. The demand to supply ratio is used to determine changes in price, following a linear function (this is price responsiveness—how much price changes due to an imbalance between demand and supply). Changes in relative price affect both demand and supply. For example, an increase in price incentivizes builders to construct more homes, while discouraging buyers from purchasing.

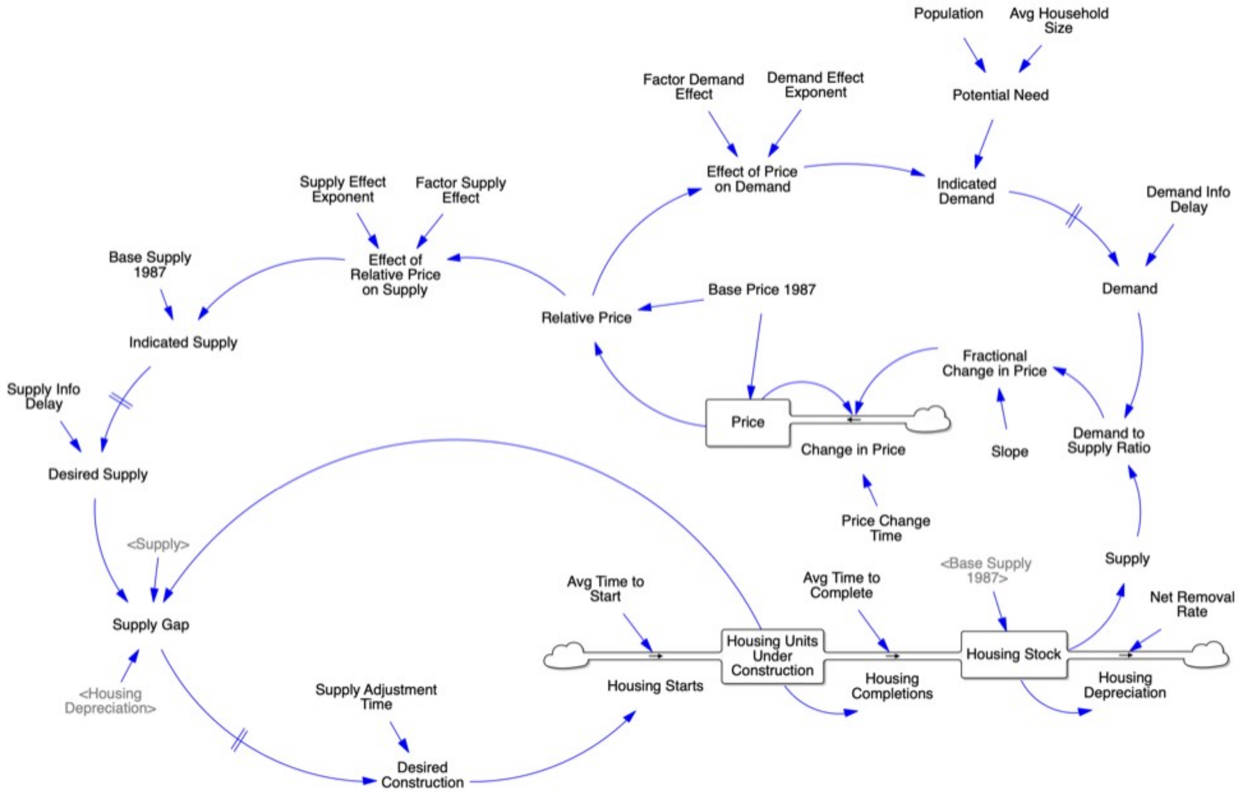


Figure 6: The commodity cycle: supply and demand regulated by price.

Third, I added a labor dynamics structure (see Figure 7) with endogenous labor productivity. The labor force stock has a hiring inflow and a leaving outflow. Hiring depends on labor shortage or surplus, which is the difference between the current labor force and the desired labor force. The desired labor force is determined from desired construction and the inverse of labor productivity. Since labor productivity in this model equals units completed over the labor force, the inverse of that is the number of workers needed per home. Labor productivity in this model (housing completions divided by the labor force) differs from the indices plotted as reference modes, which are based on value in dollars of output over worker hours in a year.

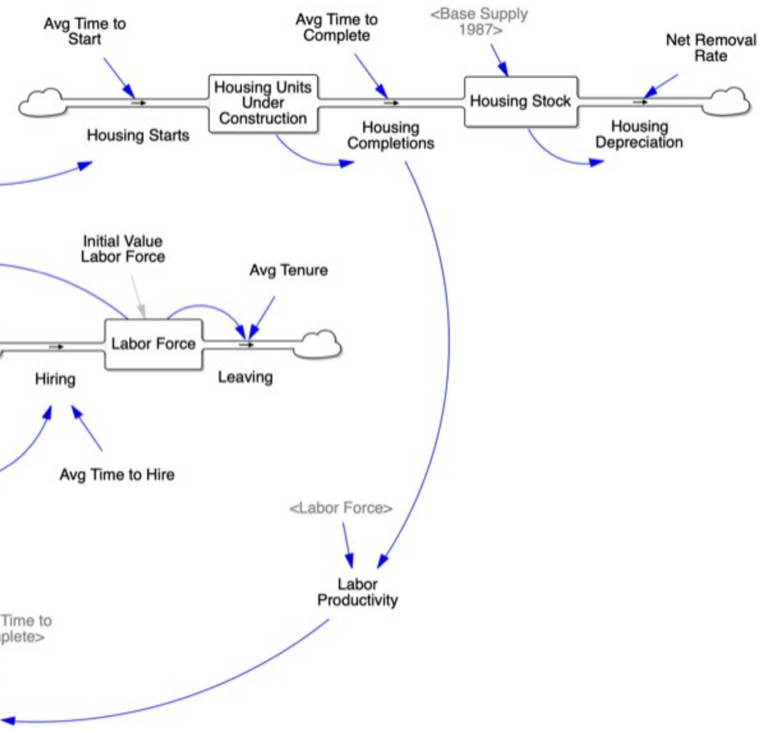


Figure 7: Labor structure in the model with endogenous labor productivity.

Fourth, I incorporated a learning structure as shown in Figure 8. The labor force has some level of accumulated knowledge due to the knowledge level of its workers. Inflows in knowledge come from hiring and from learning on the job. Knowledge loss (outflow) occurs when people leave and take their knowledge with them. The average knowledge of an employee feeds into the industry's potential to complete homes, which is formulated with a modified Cobb-Douglas ([45]) production function $Y = AK^{1-\alpha}L^{\alpha}$. In this model, A represents the baseline labor required, K represents the labor force, L represents knowledge, and α represents the importance of knowledge.

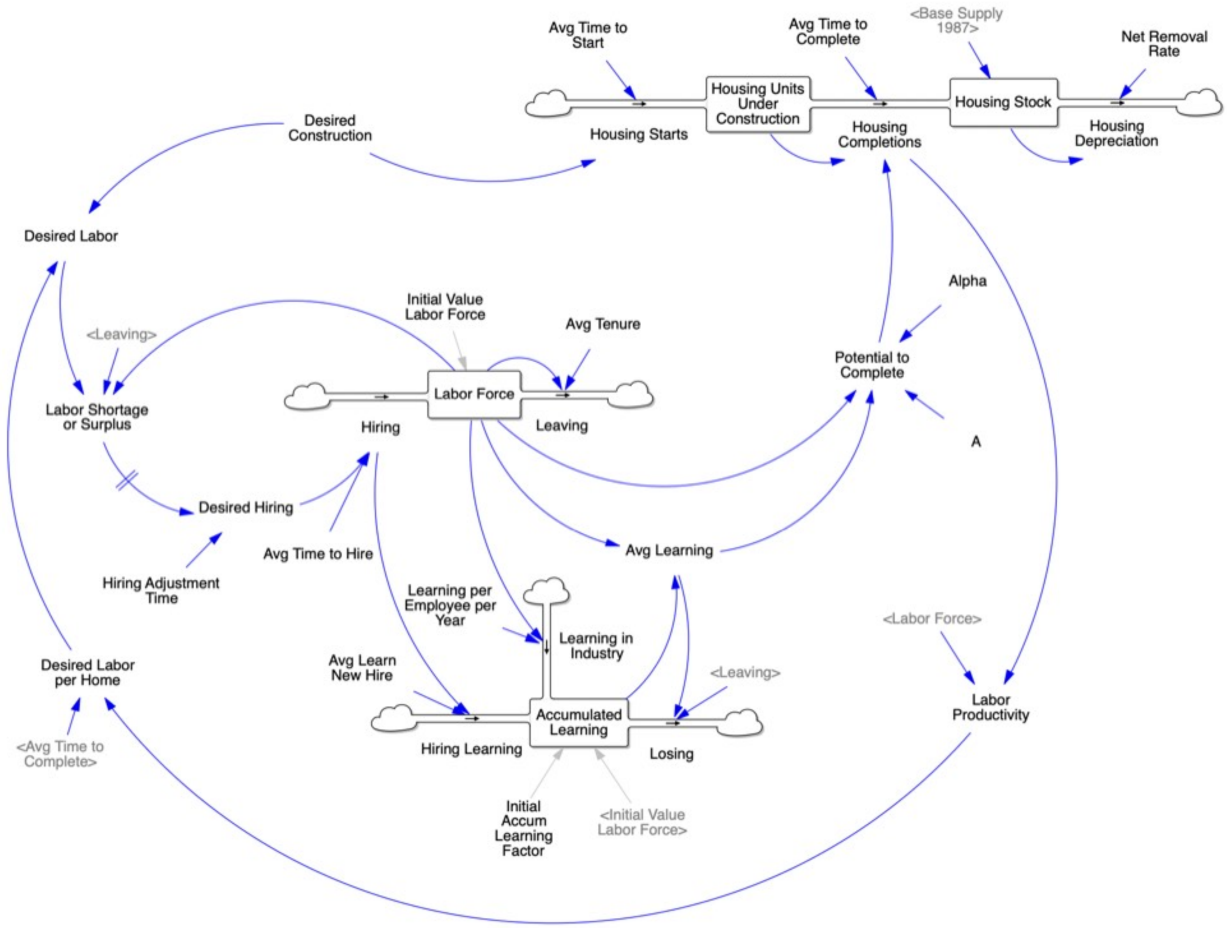


Figure 8: Learning structure in the model.

Finally, I added a backlog structure so that the stock of housing units under construction was reasonably bounded. For example, a builder might hold off on starting new projects while they have a backlog. The full model, including backlog, is shown in Figure 9.

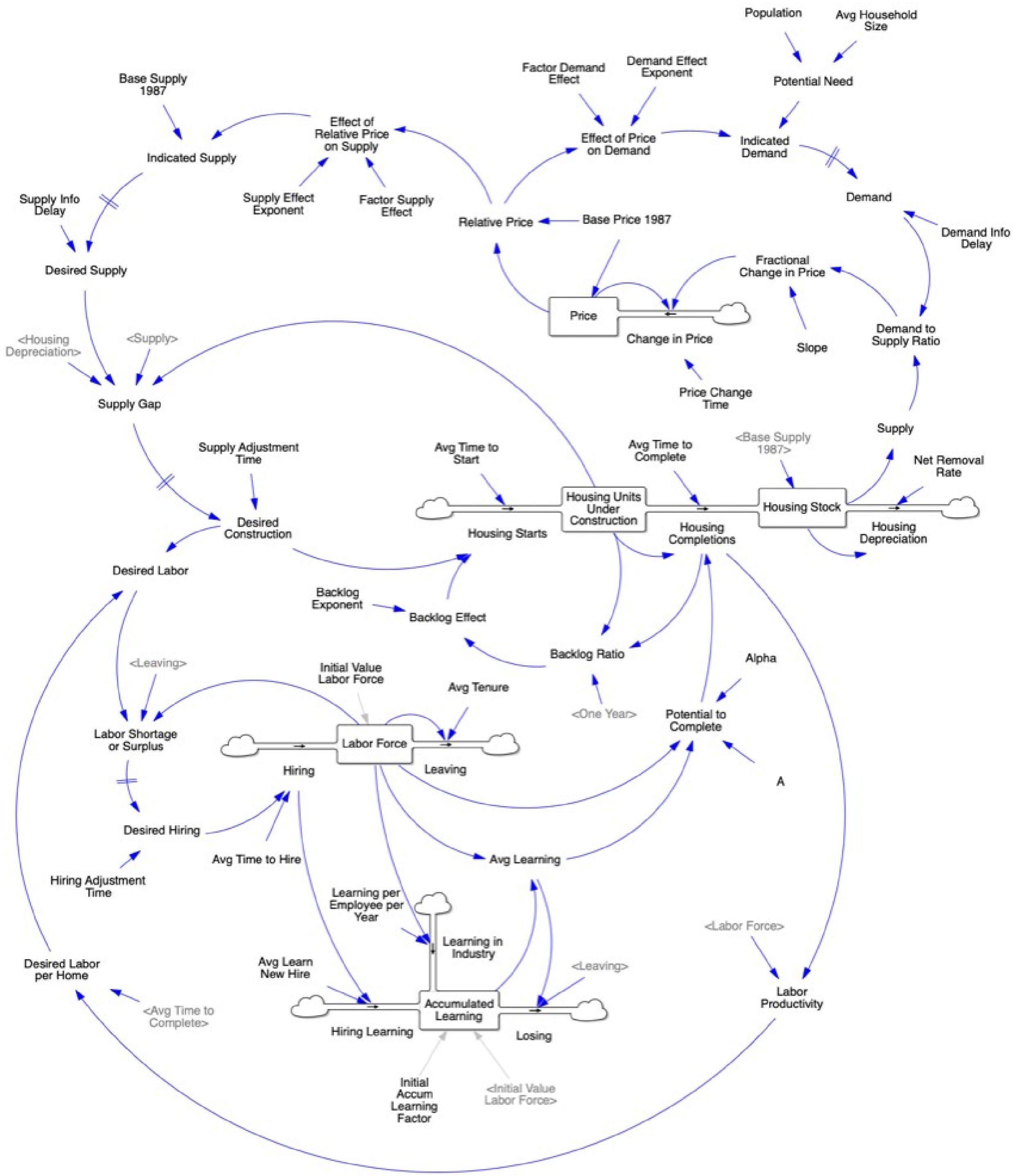


Figure 9: Full model structure.

The model structure was put into equilibrium and subjected to several tests to ensure that it produced expected behavior. For example, a demand shock from equilibrium (doubling at some time t) would result in higher prices and increased new supply, eventually reaching equilibrium again. However, a potential limitation of these tests is that they were primarily focused on the supply, demand, and construction pipeline sections of the model.

2.4 Calibration and parameter optimization

Exogenous data (population and average household size) as well as historical data for calibration variables were input from Excel files. Calibration was performed in Vensim with the Powell optimizer and multiple random restarts.

Partial calibrations were used to determine some initial model parameters. I partially calibrated the construction pipeline first, then used those parameter values to calibrate the demand and supply loops. In addition to helping me further understand the model structure, the partial calibrations informed reasonable minimum and maximum boundary values for calibrating the rest of the model.

Each industry model was calibrated separately to find the parameter values that reproduced actual, historical data. I calibrated six variables against actual data: housing starts, units under construction, completions, housing stock, price, and labor force.

The calibration weights of these variables were set as the inverse of the standard deviation of the actual data series. These weights took care of the order-of-magnitude differences in scale between the variables. For example, in the multiple-family industry there are tens of millions of homes in the housing stock, tens of thousands of workers in the labor force, and the price index is in the hundreds. I collected errors between simulated and actual data in the model. I found that re-running calibrations with new weights that are the inverse of the standard deviation of errors resulted in no or negligible changes in parameter values, so I decided to continue using the initial weights in the interest of time. Please see Table A1 in the Appendix for the weights used in calibration.

I found the optimal values and sensitivity ranges for twenty parameters through calibration:

- Avg Tenure
- Learning per Employee
- Avg Knowledge New Hire
- A
- Alpha
- Hiring Adjustment Time
- Avg Time to Hire
- Avg Time to Complete
- Avg Time to Start
- Backlog Exponent
- Slope
- Net Removal Rate
- Demand Info Delay
- Factor Demand Effect
- Demand Effect Exponent
- Factor Supply Effect
- Supply Effect Exponent
- Supply Info Delay
- Supply Adjustment Time
- Init Accum Knowledge Factor

Labor productivity is endogenous and was not calibrated to, though actual data exists. This allows us to see if the model replicates labor productivity endogenously. In addition, labor productivity in this model is equal to housing completions divided by the labor force and both of these variables are being calibrated to; calibrating to labor productivity as well would not only be redundant but also potentially overweight these variables' importance.

I created custom graphs to compare simulated and actual data, and I also collected the difference (errors) between simulated and actual data inside the model. Though payoff was the main metric used by Vensim in calibration, I also reported other measures, such as the mean absolute percent error (MAPE).

2.5 Aggregate data checks

I performed an additional check by totaling the simulated values from the two industry models and comparing them to actual aggregate data. For example, the simulated labor force numbers from the industry models were summed and compared to the actual total labor force. I calculated measures such as the mean absolute percent error for these comparisons to quantify how closely they aligned.

2.6 Scenario tests

I tested several scenarios, in particular focusing on the differences between the industries: knowledge importance, workforce stability or turnover, and times to start or complete a home. I examined how these scenarios affected labor productivity and the labor force as well as other variables such as housing stock and price.

The first scenario I tested investigated the outcomes if multiple-family residential construction were to depend on worker knowledge the same way that the single-family industry does. I tested this by swapping the respective calibrated multiple-family and single-family Alpha values. My hypothesis was that labor productivity would decrease for multiple-family, indicating how each industry depends on worker knowledge.

Another related scenario that I tested investigated what would happen as Alpha decreases in both industries. Decreasing Alpha would simulate less reliance on the knowledge and learning of workers; in a way, this test simulates having a higher level of project standardization—potentially even higher adoption of industrialized construction methods such as standardized designs, off-site construction, manufactured homes, modular construction, pre-fabrication, or the use of structural building components. My hypothesis was that completions and labor productivity would increase, making a case for further adoption of industrialized construction methods.

A third scenario test examined workforce stability and turnover, particularly in the single-family industry. I increased the Avg Tenure in the single-family model, giving it the value from the calibrated multiple-family model. My hypothesis was that labor productivity would increase and labor force would drop in the single-family model, indicating that potentially effective policy levers might include labor force retention measures.

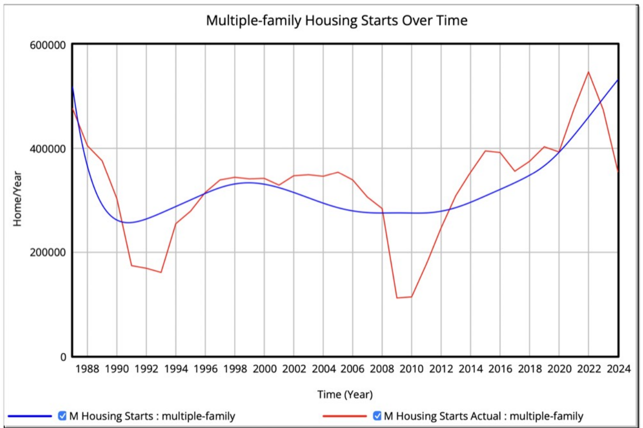
I also tested what would happen to completions, housing stock, and price if the Avg Time to Complete were cut in half. My hypothesis was that completions and housing stock would increase, and price growth would be curbed. Having shorter completion times simulates the adoption of new construction technologies that are intended to build homes faster. Similarly, I tested quicker start times by dividing the Avg Time to Start in half. Having shorter start times simulates quicker planning and permitting approval processes, another potential policy lever.

3 Results

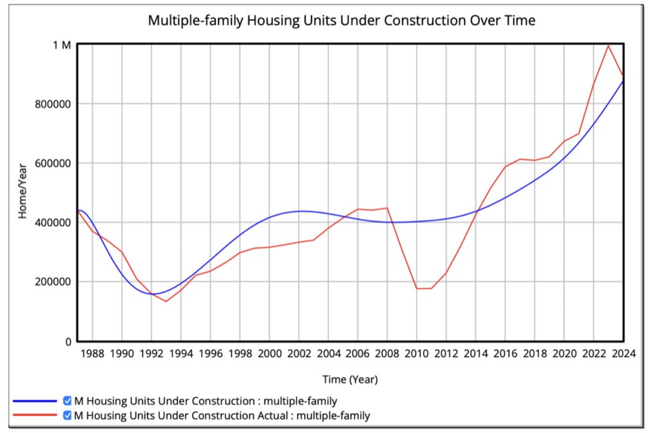
3.1 Calibration

3.1.1 Multiple-family model calibration

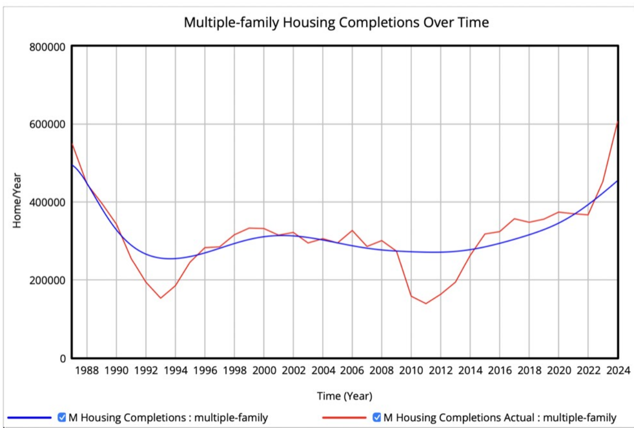
Figure 10 shows the graphical comparisons between simulated and actual data for selected variables in the multiple-family model.



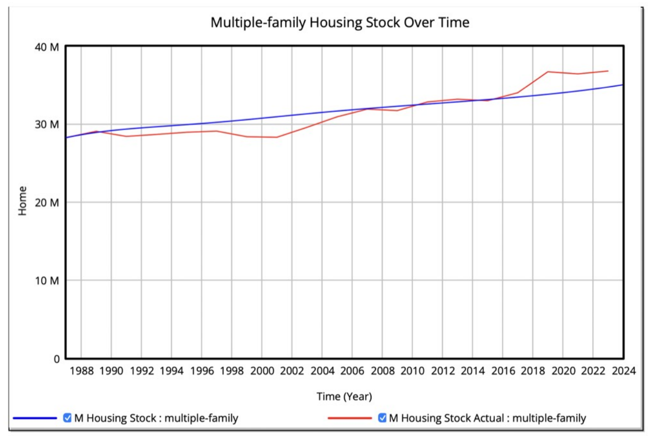
(a) Housing starts



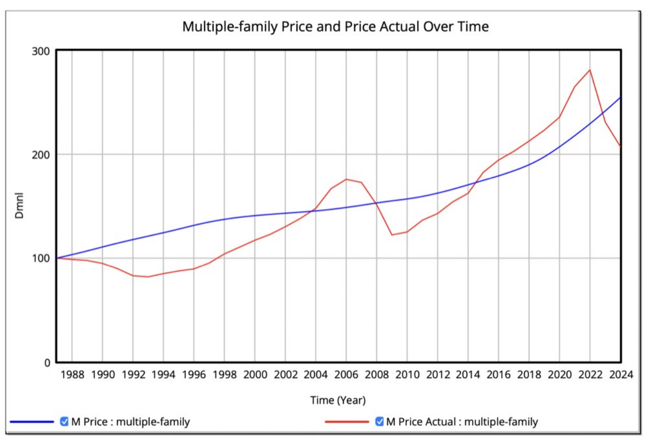
(b) Housing units under construction



(c) Housing completions



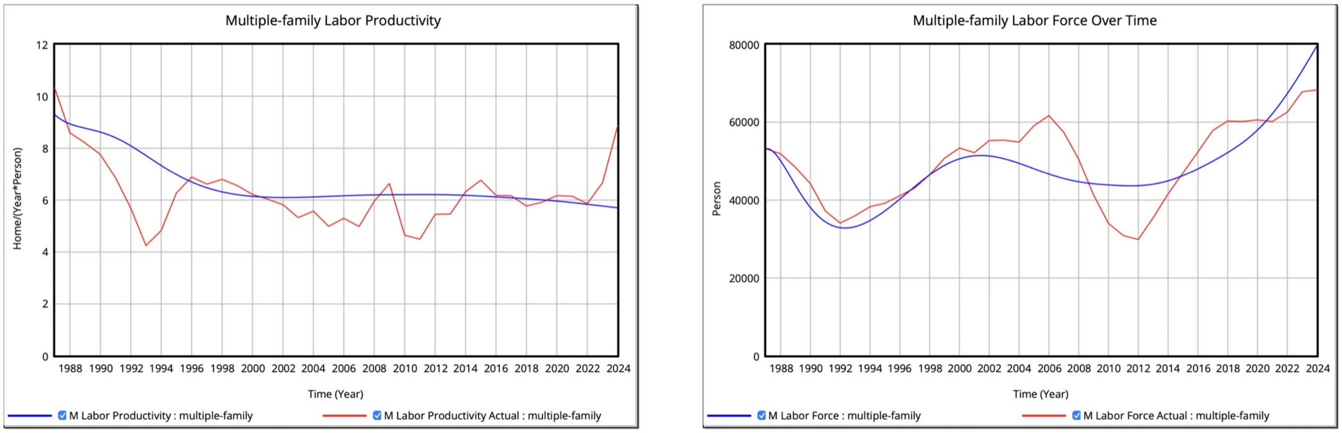
(d) Housing stock



(e) Price

Figure 10: Calibration graphs for the multiple-family model. Simulated data in blue and actual data in red.

The multiple-family model was able to reproduce the construction pipeline and labor dynamics. It was also capable of endogenously reproducing labor productivity, though missing some of the volatility. Labor productivity and labor force are shown in Figure 11.



(a) Endogenous labor productivity

(b) Labor force

Figure 11: Labor productivity and labor force for the calibrated multiple-family model. Simulated data are in blue and real data in red.

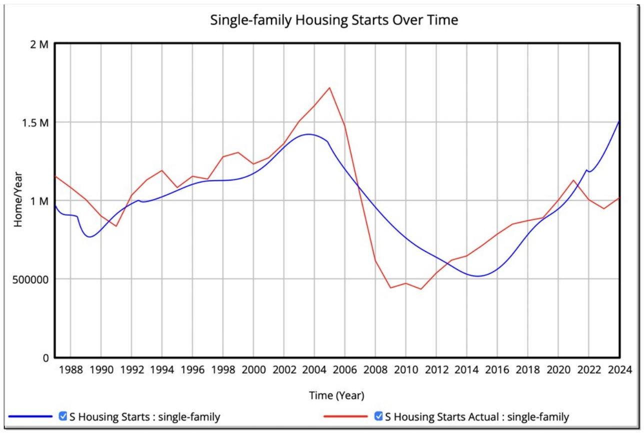
Table 3 shows statistics for how well the calibrated multiple-family industry parameters measure up with the actual data.

Table 3: Payoff components for multiple-family simulated vs. actual data

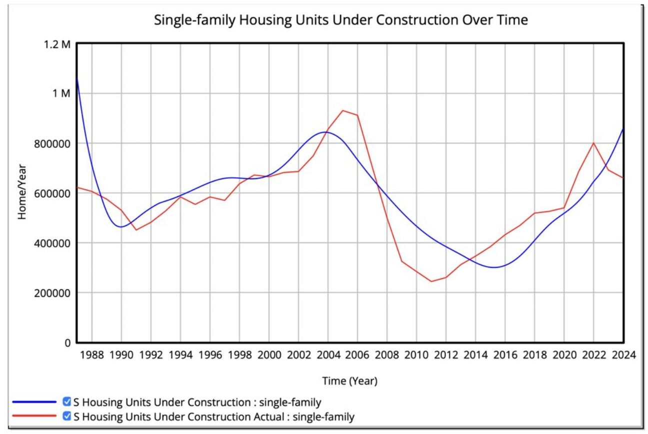
Calibration Variable	**Multiple-family Simulated vs. Actual Data**	
	MAPE	$\mathbf{R^2}$
Housing Starts	23.1%	0.49
Housing Units Under Construction	22.7%	0.81
Housing Completions	16.2%	0.70
Housing Stock	3.4%	0.77
Labor Force	10.9%	0.61
Price	18.3%	0.75

3.1.2 Single-family model calibration

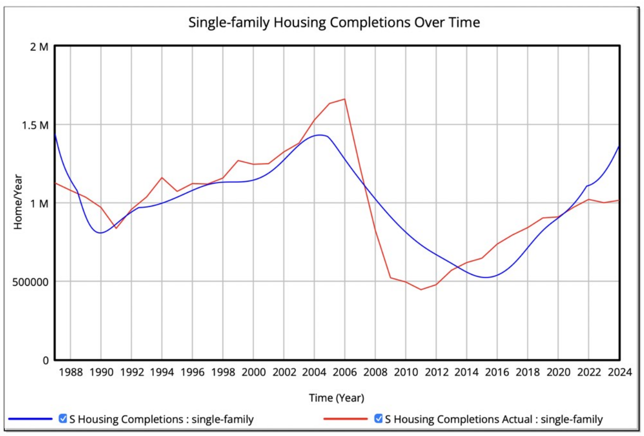
Figure 12 shows selected visual calibrations for the single-family model. The model was able to reproduce the labor dynamics and construction pipeline in the actual data, as well as endogenously reproduce labor productivity, for the single-family industry.



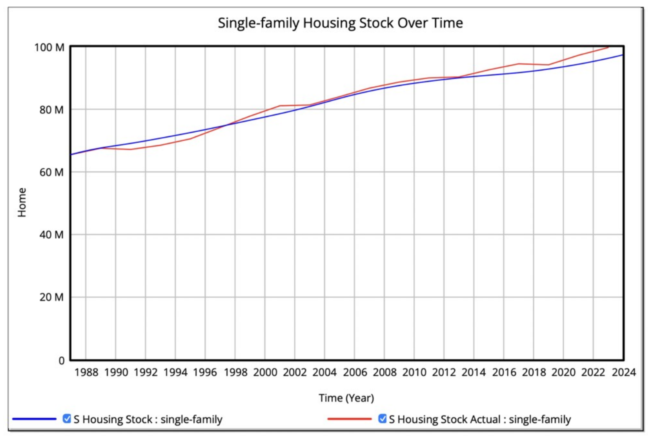
(a) Housing starts



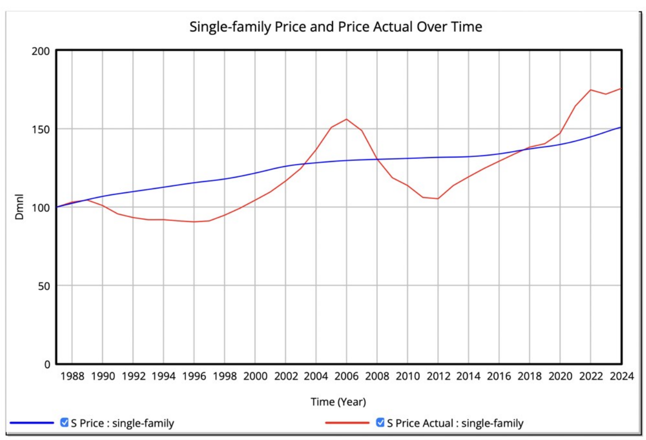
(b) Housing units under construction



(c) Housing completions



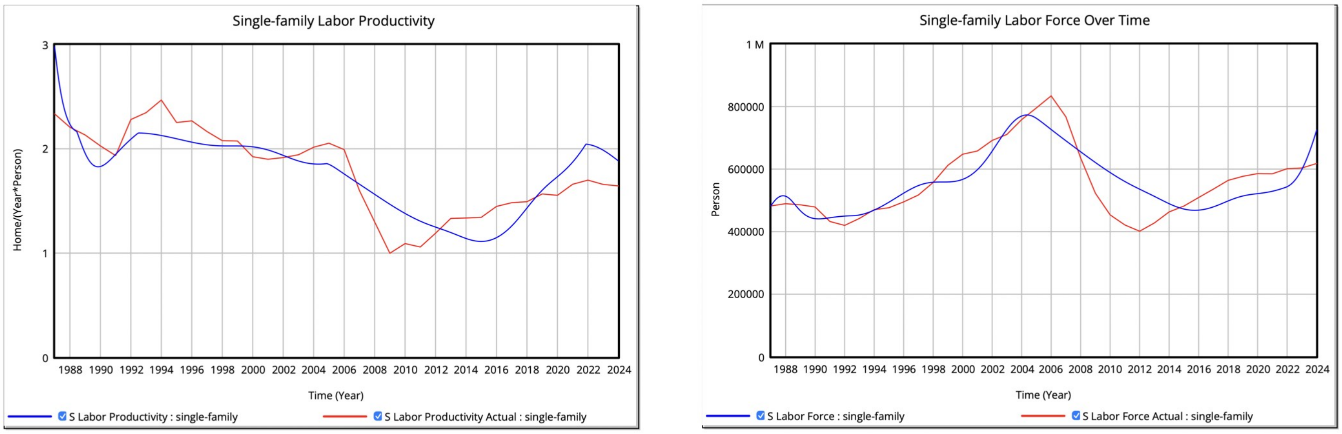
(d) Housing stock



(e) Price

Figure 12: Calibration graphs for the single-family model. Simulated data in blue and real data in red.

The simulated and actual labor productivity and labor force for the single-family industry are shown in Figure 13.



(a) Endogenous labor productivity

(b) Labor force

Figure 13: Labor productivity and labor force for the calibrated single-family model. Simulated data are in blue and actual data in red.

Table 4 shows the fit statistics between simulated and actual data for the single-family model.

Table 4: Payoff components for single-family simulated vs. actual data

Calibration Variable	**Single-family Simulated vs. Actual Data**	
	MAPE	$\mathbf{R^2}$
Housing Starts	19.1%	0.60
Housing Units Under Construction	18.9%	0.49
Housing Completions	16.3%	0.68
Housing Stock	1.7%	0.97
Labor Force	9.1%	0.69
Price	12.5%	0.54

3.1.3 Aggregate check

Table 5 shows the results of combining the multiple-family and single-family industries' simulated data and comparing to actual aggregate data. Overall, the results are reasonable, adding another check to support the usefulness of the model. Actual data for the aggregate price was not directly available. Instead, a weighted average from the actual multiple-family and single-family data was calculated. Other variables were directly available in aggregate.

Table 5: Combined multiple- and single-family simulated data vs. actual aggregate data

Calibration Variable	**Aggregate Simulated vs. Actual Data**	
	MAPE	$\mathbf{R^2}$
Housing Starts	17.7%	0.52
Housing Units Under Construction	13.9%	0.63
Housing Completions	18.8%	0.70
Housing Stock	1.6%	0.97
Labor Force	8.9%	0.682
Price	13.8%	0.65

3.2 Parameter values

Table 6 reports the resulting parameter values for the calibrated multiple-family and single-family industries. Note in particular the differences between the two models for the variables Avg Tenure, A (the base labor requirement), and Alpha (the importance of knowledge/learning).

Table 6: Parameter values for calibrated multiple- and single-family industries.

Parameter	Multiple-family	Single-family
Avg Tenure	2.32	0.50
Learning per Employee per Year	1.00	3.42
Avg Knowledge New Hire	10.20	22.20
A	18.60	32.70
Alpha	0.13	0.28
Hiring Adjustment Time	3.00	2.54
Avg Time to Hire	1.37	0.28
Avg Time to Complete	0.36	0.57
Avg Time to Start	0.83	0.97
Backlog Exponent	0.00	2.59
Slope	0.26	0.32
Net Removal Rate	4.03e-03	1.50e-03
Demand Info Delay	0.75	7.91e-03
Factor Demand Effect	1.30	1.14
Demand Effect Exponent	1.59e-05	0.09
Factor Supply Effect	1.05	1.04
Supply Effect Exponent	0.32	1.11
Supply Info Delay	6.99	4.79
Supply Adjustment Time	2.37	3.73
Initial Accum Knowledge Factor	309.40	82.80

The learning or knowledge-related parameters in Table6 are in arbitrary index units specific to each sector's calibration and are not directly comparable across industries.

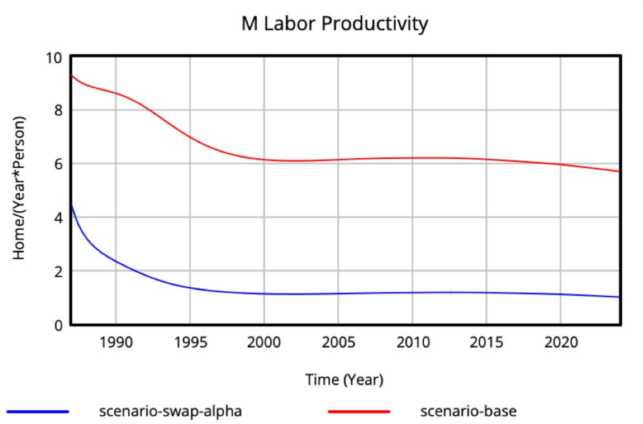
Table A2 in the Appendix shows the sensitivity ranges (the range of parameter values over which the payoff degrades by 4 units from optimal, roughly corresponding to 95% confidence intervals), while Table A3 contains the values and ranges for the single-family parameters.

3.3 Scenario tests

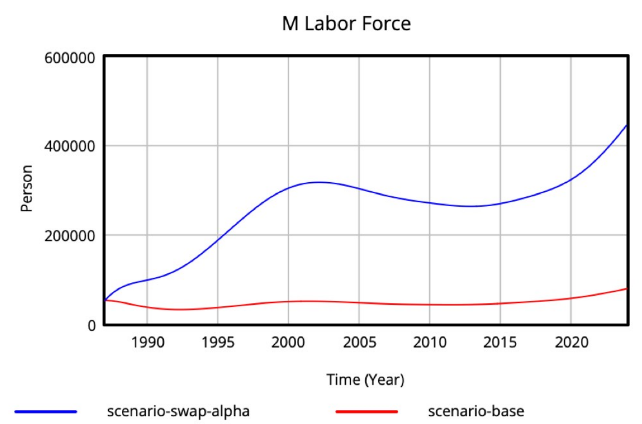
3.3.1 Swap Alpha values between industries

I switched the Alpha values for the multiple-family and single-family industries and re-ran the simulations, keeping the other parameters at their calibrated values. The Alpha for the multiple-family industry was changed from approximately 0.13 to approximately 0.28; the Alpha for the single-family industry was adjusted from approximately 0.28 to approximately 0.13.

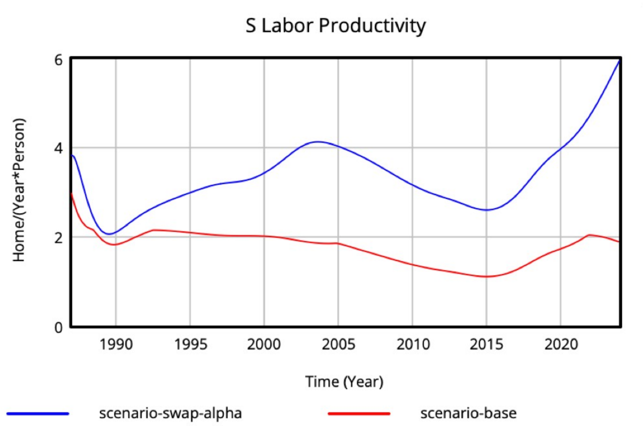
Figure 14 shows that for the multiple-family industry, the higher Alpha (from the single-family industry) results in a lower labor productivity and a larger labor force. Meanwhile, a lower Alpha for the single-family industry results in increased labor productivity and decreased labor force.



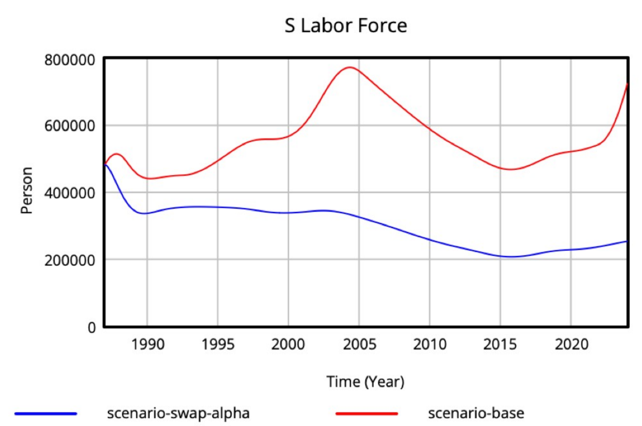
(a) Multiple-family labor productivity with higher Alpha value from single-family



(b) Multiple-family labor force with higher Alpha value from single-family



(c) Single-family labor productivity with lower Alpha value from multiple-family

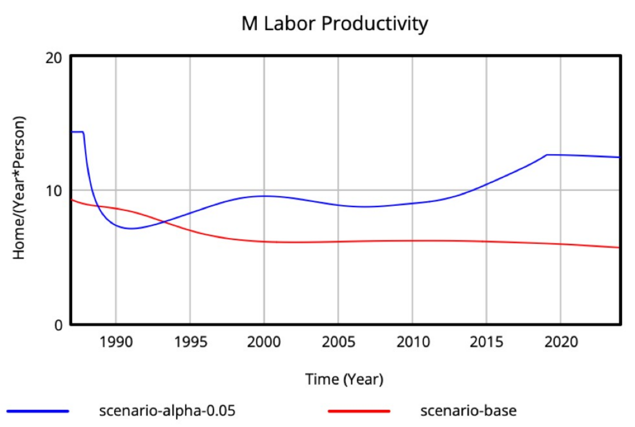


(d) Single-family labor force with lower Alpha value from multiple-family

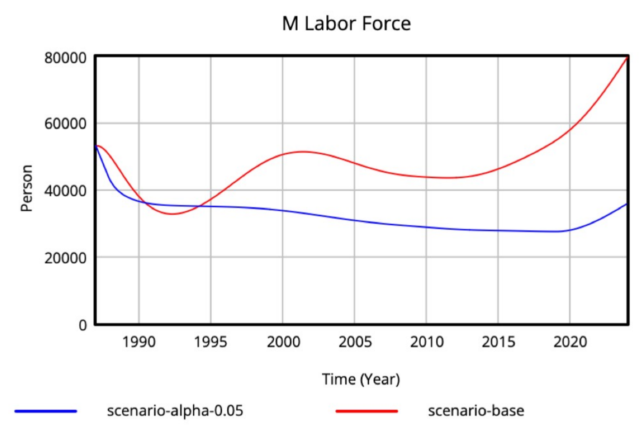
Figure 14: Results of swapping Alpha values between the multiple- and single-family industries.

3.3.2 Decreased reliance on knowledge (Alpha)

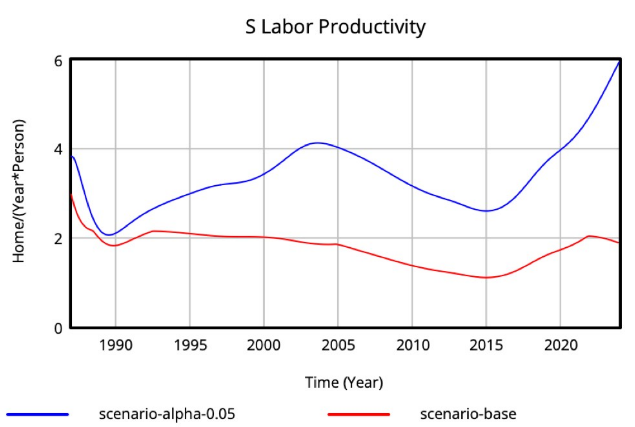
First, I used a SyntheSim interactive simulation to decrease Alpha. In the multiple-family industry, as Alpha decreased, labor productivity increased and labor force decreased. Similarly, in the single-family industry, labor productivity increased and labor force decreased. Next, I tried setting each industry's Alpha value equal to 0.05. In each industry, labor productivity increased and labor force decreased. The resulting graphs from setting Alpha to 0.05 are shown in Figure 15.



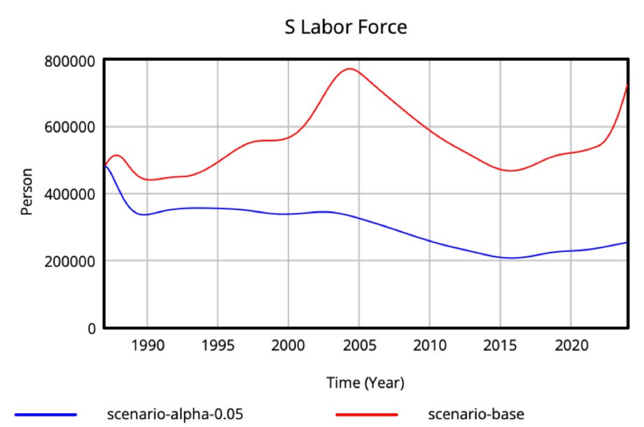
(a) Multiple-family labor productivity with Alpha = 0.05



(b) Multiple-family labor force with Alpha = 0.05



(c) Single-family labor productivity with Alpha = 0.05

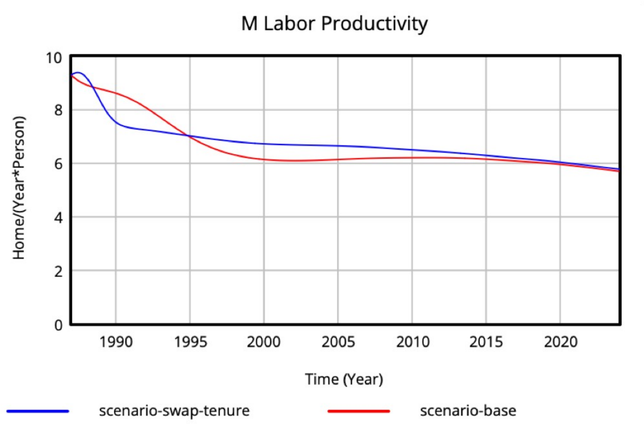


(d) Single-family labor force with Alpha = 0.05

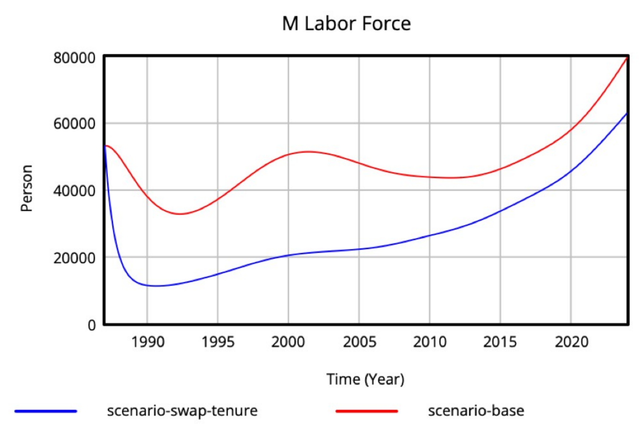
Figure 15: Results from setting Alpha = 0.05 in the multiple- and single-family industries

3.3.3 More stable workforce (longer tenure) in the single-family industry

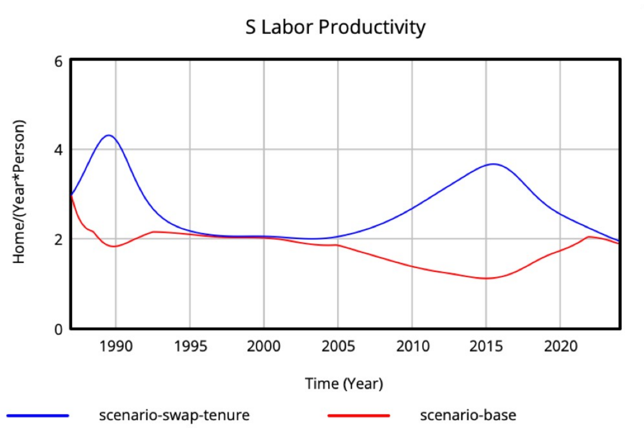
I increased the Avg Tenure for the single-family industry from 0.50 years (about 6 months) to 2.32 years, giving it the value obtained from the multiple-family industry. As an additional test, I also gave the multiple-family industry the single-family Avg Tenure value. In other words, the single-family industry was given a higher Avg Tenure and the multiple-family industry was given a lower one. For the single-family industry, the higher Avg Tenure resulted in higher labor productivity and a smaller labor force. For the multiple-family industry, the lower Avg Tenure resulted in not much change in labor productivity because both housing completions and labor force decreased. Figure 16 shows the results from swapping the Avg Tenure values.



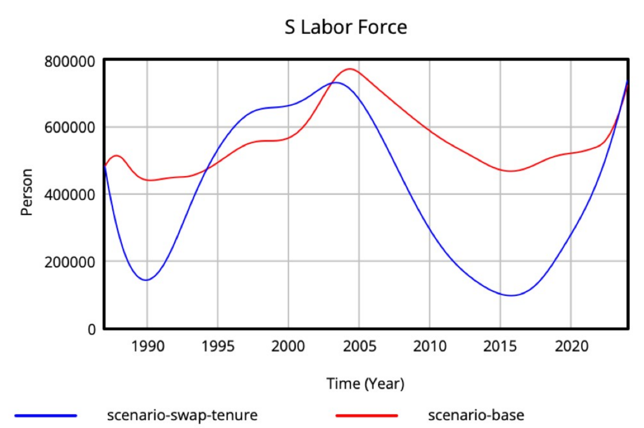
(a) Multiple-family labor productivity with lower Avg Tenure from the single-family industry



(b) Multiple-family labor force with lower Avg Tenure from the single-family industry



(c) Single-family labor productivity with higher Avg Tenure from the multiple-family industry

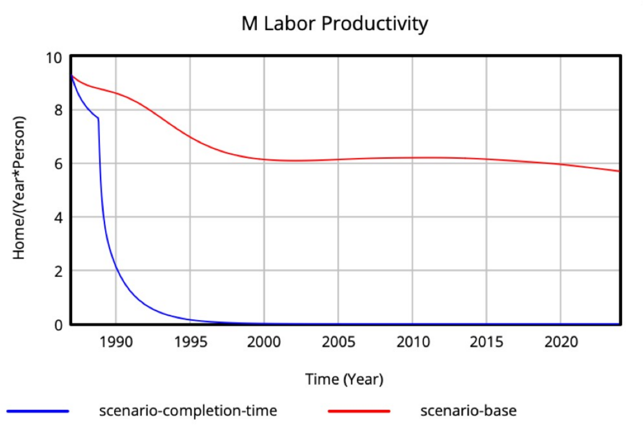


(d) Single-family labor force with higher Avg Tenure from the multiple-family industry

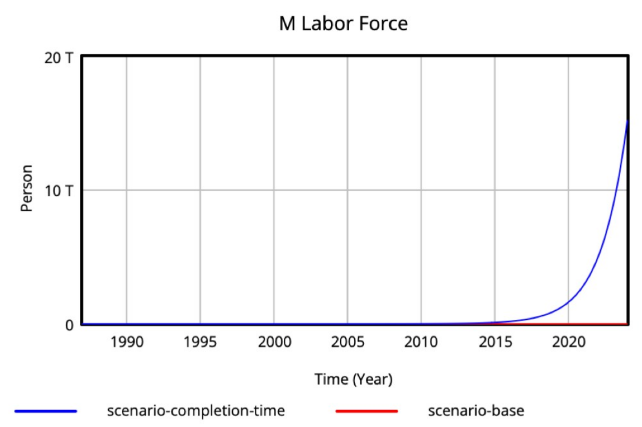
Figure 16: Results from swapping Avg Tenure in the multiple- and single-family industries.

3.3.4 Faster completions

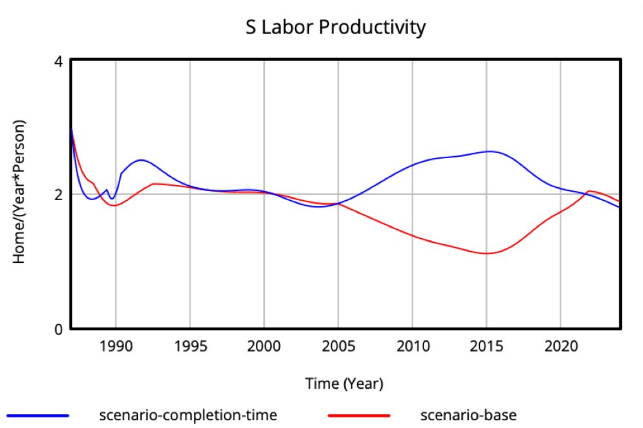
Each Avg Time to Complete value was divided in half, so the multiple-family value went from approximately 0.36 to approximately 0.18, and the single-family value went from approximately 0.57 to approximately 0.29. In the multiple-family industry, labor productivity decreased because the labor force increased. Meanwhile, in the single-family industry, labor productivity increased and the labor force decreased. The results appear to indicate that faster completion times may be useful to seek in the single-family industry, but might cause runaway behavior in the multiple-family industry without other adjustments such as the backlog exponent. Figure 17 displays these results.



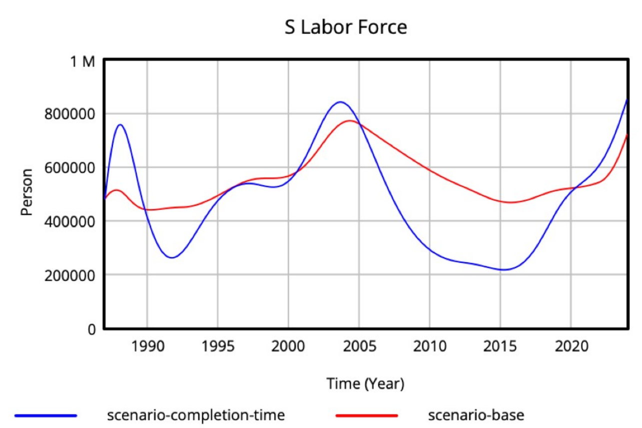
(a) Multiple-family labor productivity with decreased Avg Time to Complete



(b) Multiple-family labor force with decreased Avg Time to Complete



(c) Single-family labor productivity with decreased Avg Time to Complete



(d) Single-family labor force with decreased Avg Time to Complete

Figure 17: Results from reducing Avg Time to Complete in the multiple- and single-family industries.

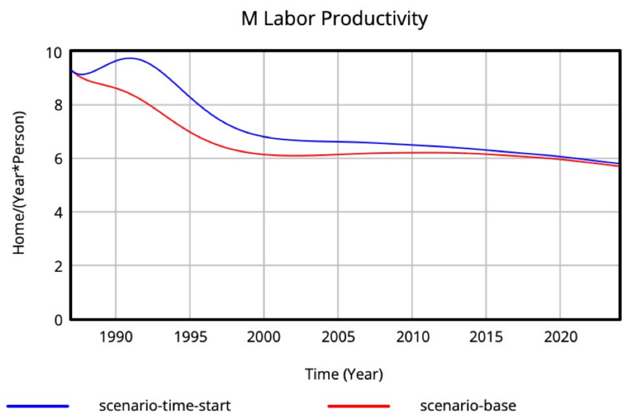
In halving the completion times, housing stock increases and price decreases in both the multiple-family and single-family industries. However, these outcomes are relatively slight (shown in Table 7).

Table 7: End time (2024) results from halving the Avg Time to Complete compared to the base scenario

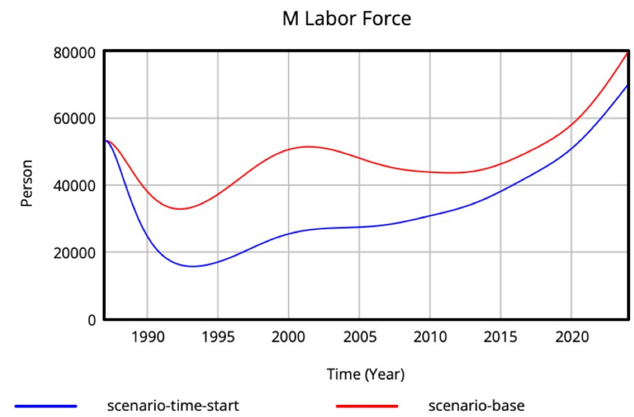
	Multiple-family		**Single-family**	
	Housing Stock	**Price Index**	**Housing Stock**	**Price Index**
Shorter Avg Time to Complete	35.38M	241.67	98.06M	150.30
Base (calibrated)	35.07M	254.72	97.39M	151.00

3.3.5 Quicker start times

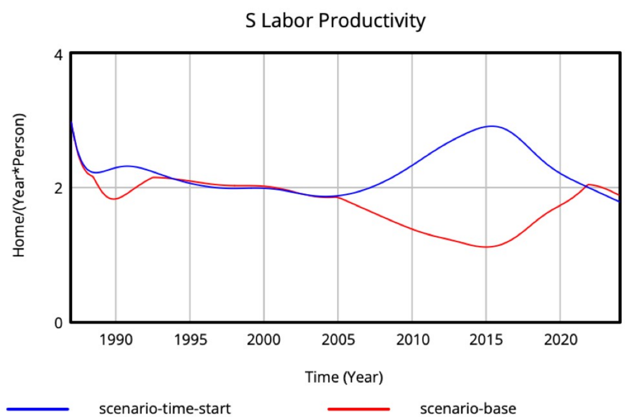
Each Avg Time to Start value was divided in half, so the multiple-family value went from approximately 0.83 to approximately 0.41, and the single-family value went from approximately 0.97 to approximately 0.49. In the multiple-family industry, labor productivity decreased because both completions and the labor force decreased. Housing starts did increase but units seemed to accumulate in the under construction stock. Prices increased as housing stock decreased. Meanwhile, in the single-family industry, labor productivity increased and the labor force decreased. Housing stock and price were seemingly unaffected. The results appear to indicate that faster start times may not be an effective policy lever on its own. See Figure 18 for labor productivity and labor force under reduced start times.



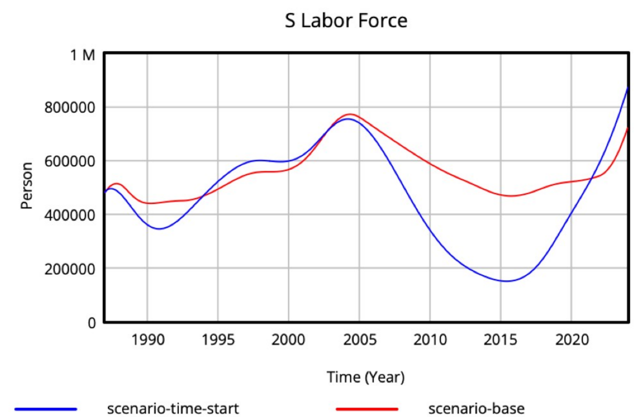
(a) Multiple-family labor productivity with decreased Avg Time to Start



(b) Multiple-family labor force with decreased Avg Time to Start



(c) Single-family labor productivity with decreased Avg Time to Start



(d) Single-family labor force with decreased Avg Time to Start

Figure 18: Results from reducing Avg Time to Start in the multiple- and single-family industries.

4 Discussion

This study contributes a new perspective on the decline in construction labor productivity, focusing on learning and labor force in the multiple-family and single-family residential construction industries. I calibrated the same model structure for each industry with its respective data, enabling comparisons between the two industries. The model was able to replicate industry dynamics reasonably well for both industries including the construction pipeline, commodity cycle, and labor force; it also reproduced labor productivity endogenously. These results and the scenario tests point to increasing the level of standardization in the single-family residential construction industry in order to increase labor productivity.

4.1 Key takeaways

Independent calibration revealed key differences related to learning and labor force between the two industries. The single-family industry is about twice as sensitive to workforce knowledge than the multiple-family industry—in other words, worker knowledge is much more important in the single-family industry. The base labor requirement is also almost double for the single-family industry compared to the multiple-family industry. In addition, employees leave quickly in the single-family industry, staying only about 6 months on average, while the multiple-family industry has a far more stable workforce. Furthermore, the single-family industry hires employees quickly, so people are almost constantly coming and going in that industry, impacting knowledge accumulation and the average knowledge of a worker in the industry.

These differences point back to Figure 4 which showed that the single-family industry is more fragmented than the multiple-family industry, with more and smaller companies. This industry structure reflects more standalone, custom projects for single-family homes. In contrast, the multiple-family industry can build units with batch processes that are more standardized and with larger economies of scales due to shared foundations, walls, and permits. Larger companies with larger projects in the multiple-family industry may also explain the higher workforce tenure.

The test scenarios also supported the conclusion that higher fragmentation and turnover hold back the single-family industry. Experiments with Alpha (the importance of knowledge) showed that if the single-family industry had the standardization possible through the larger companies and batch-style construction processes of the multiple-family industry, the single-family industry could rely less on the knowledge of individual workers and would achieve higher labor productivity. Furthermore, experiments with the average employee tenure showed that a more stable workforce with lower turnover—perhaps more easily achievable with longer projects and larger companies with more resources—would help the single-family industry increase its labor productivity.

This study concludes that in order for the construction sector's labor productivity to follow the path of higher productivity sectors like manufacturing, similar standardization and reliance on process (rather than the knowledge of individual workers) may be necessary.

4.2 Limitations

In order for labor productivity to be endogenous, the operationalization of the labor productivity variable had to be different from the reference modes that were initially plotted. This difference means that the patterns in labor productivity look different, and the divergence between the multiple-family industry and the single-family industry in the model is not as stark as in the reference mode.

The model combines on-the-job learning with knowledge brought in by new hires. Accumulated knowledge and average learning ended up essentially being scaling factors in the model, not really interpretable. Another structure could potentially differentiate knowledge gain through hiring versus experience to confirm whether, for example, the single-family industry is rapidly hiring new workers with knowledge rather than accumulating knowledge with a more stable work force.

Scenario tests that resulted in increases in labor productivity appeared to be due to decreasing labor force. This may be useful in the face of labor shortages; however, increasing completions would be more desirable from the perspective of overall system behavior, as increasing the nation's housing stock would bring down prices.

Other limitations are related to data. The exogenous population and average household size data by industry are only available every other year, and thus required some interpolation. The multiple-family price index tracks institutional buyers of apartments. The index should mimic home buyers of apartments, condominiums, and other multiple-family homes overall, but may not do so exactly. The price data does not account for renting, which may be a large part of the multiple-family market in particular.

While this model captures price trends overall, it does not capture the full price dynamics. This is acceptable for this study's purposes which is not focused on price, but not as useful when testing strategies for bringing home prices down.

4.3 Future opportunities

Future work building on this study could offer further insight into construction labor productivity. The model structure already replicates important dynamics as is, but additional structure could be incorporated. For example, the new hires and experienced labor force could be differentiated, perhaps with an aging chain or co-flow type of structure. It would also be useful to model and test industry fragmentation more directly. In addition, technological investment and advancement could be separated from other types of learning. Incorporating investment and other financial variables like output value in dollars could open up more possibilities, such as accounting for labor costs and simulating a labor productivity variable that matches the BLS index. Developing and testing additional policy levers informed by industry members and policymakers will be an important next step towards reversing the labor productivity trend and ameliorating housing shortages.

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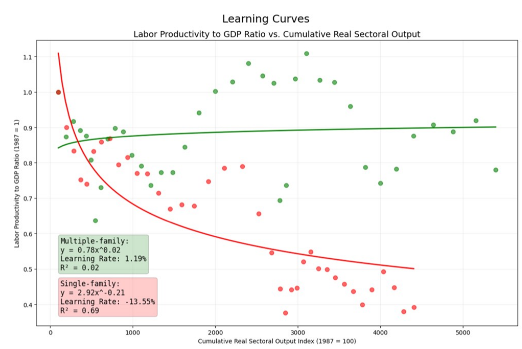
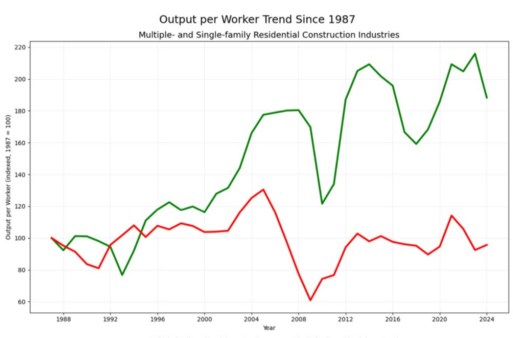
Appendix

Figures A1 through A6 contain additional reference modes I plotted.

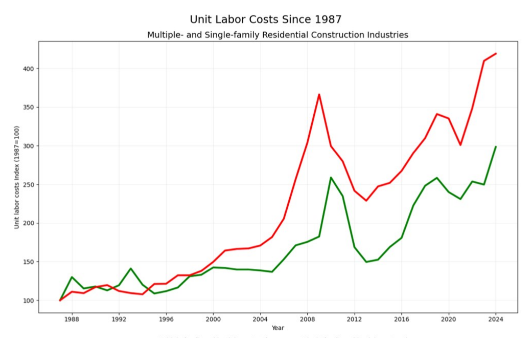
(a)



(b)

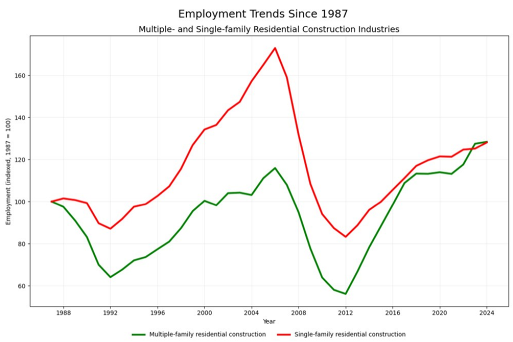


(c)

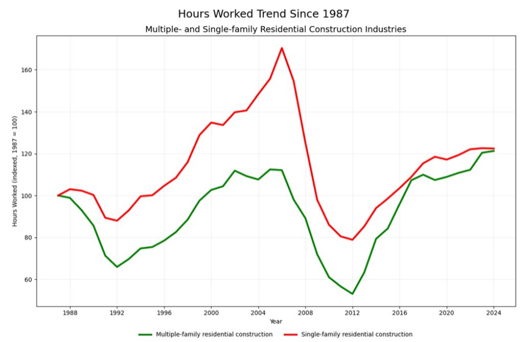


(d)

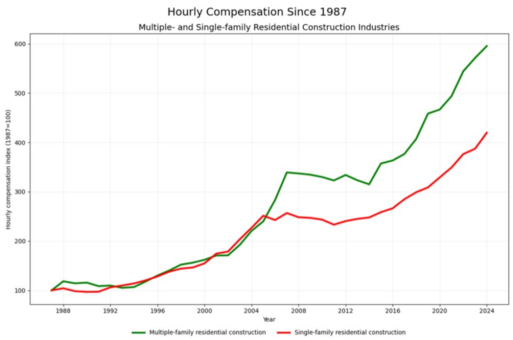
Figure A1: Reference modes A1-a – A1-d



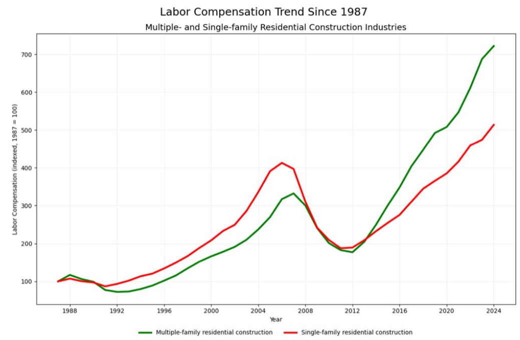
(a)



(b)

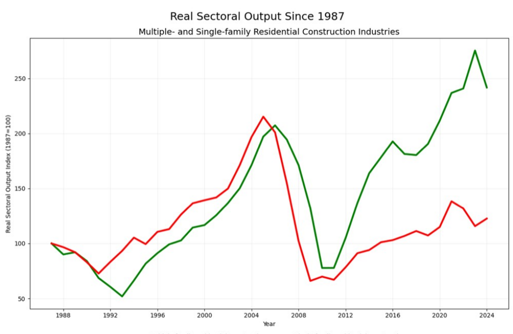


(c)

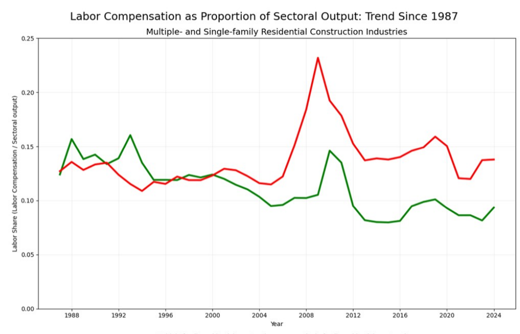


(d)

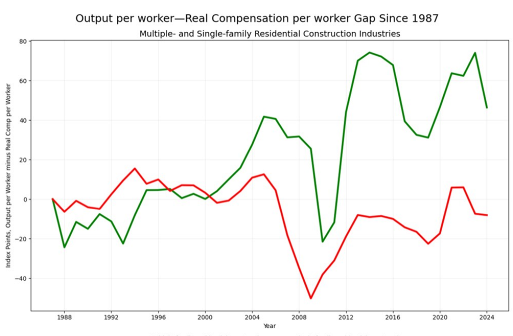
Figure A2: Reference modes A2-a – A2-d



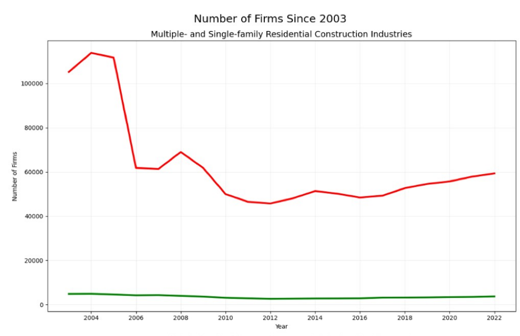
(a)



(b)

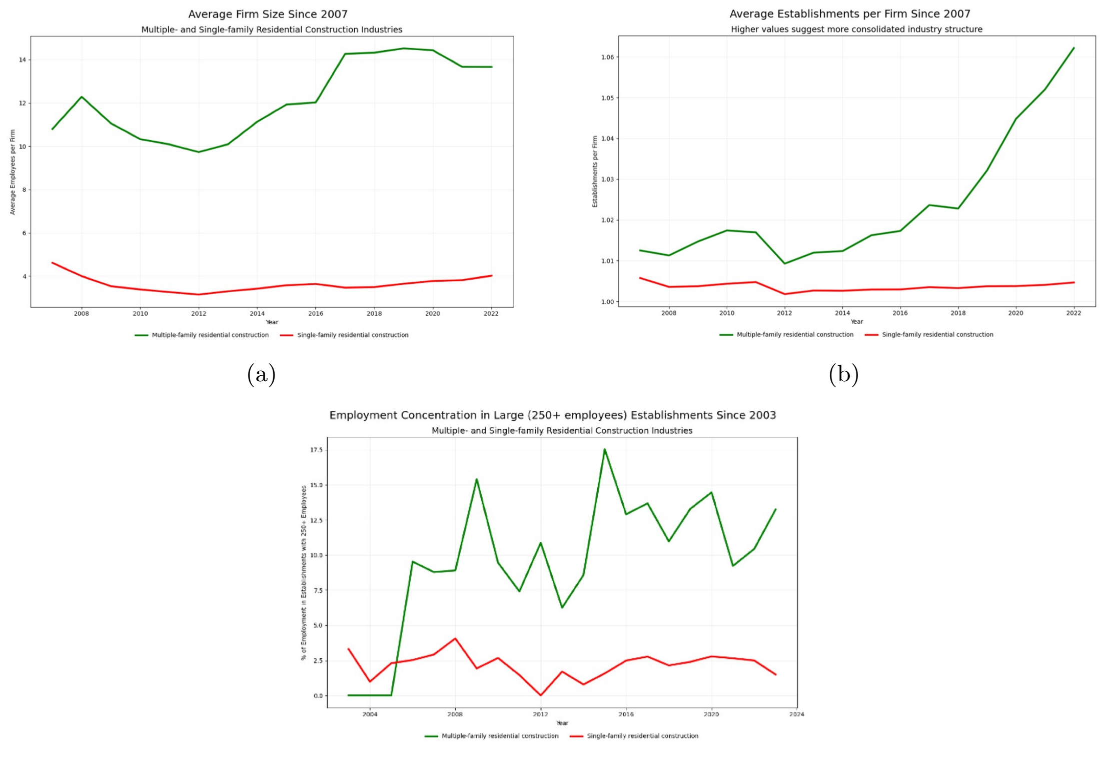


(c)



(d)

Figure A3: Reference modes A3-a – A3-d



(a) (b)

(c)

Figure A4: Reference modes A4-a – A4-d

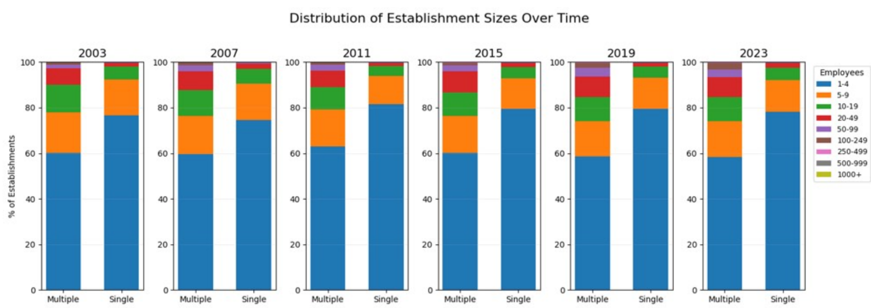


Figure A5

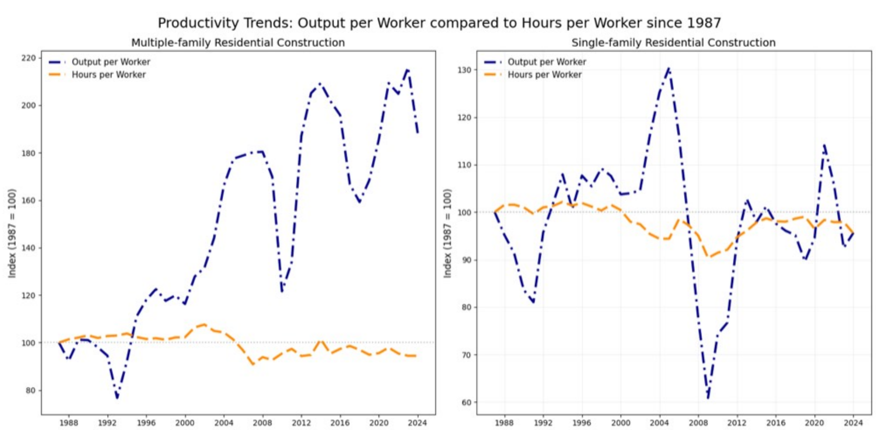


Figure A6

Table A1: Weights used for calibration (rounded)

Variable	Multiple-family			Single-family		
	Mean	SD	Weight (1/SD)	Mean	SD	Weight (1/SD)
Housing Starts	326,579	98,112	1.02e-05	1,012,184	316,374	3.16e-06
Housing Units Under Construction	410,368	211,836	4.72e-06	567,395	171,151	5.84e-06
Housing Completions	311,237	99,284	1.01e-05	1,000,158	305,822	3.27e-06
Housing Stock	31,411,000	3,004,961	3.33e-07	82,713,684	11,184,408	8.94e-08
Price	148	55	0.02	121	26	0.04
Labor Force	49,326	10,535	9.49e-05	558,126	113,185	8.84e-06

Table A2: Optimized parameters and sensitivity ranges for calibrated multiple-family model

Parameter	Multiple-family value	Sensitivity range	
		Lower bound	Upper bound
Avg Tenure	2.32	2.28	2.36
Learning per Employee per Year	1.00	1.00	4.09
Avg Knowledge New Hire	10.20	5.90	17.20
A	18.60	17.8	19.4
Alpha	0.13	0.13	0.14
Hiring Adjustment Time	3.00	2.96	3.04
Avg Time to Hire	1.37	1.36	1.39
Avg Time to Complete	0.36	0.36	0.36
Avg Time to Start	0.83	0.82	0.84
Backlog Exponent	0.00	0.00	4.80e-02
Slope	0.26	0.23	0.28
Net Removal Rate	4.03e-03	3.67e-03	4.39e-03
Demand Info Delay	0.75	0.25	1.63
Factor Demand Effect	1.30	1.29	1.31
Demand Effect Exponent	1.59e-05	0.00	1.90e-02
Factor Supply Effect	1.05	1.04	1.05
Supply Effect Exponent	0.32	0.29	0.36
Supply Info Delay	6.99	5.55	8.94
Supply Adjustment Time	2.37	1.87	3.03
Initial Accum Knowledge Factor	309.40	143.40	637.00

Table A3: Optimized parameters and sensitivity ranges for calibrated single-family model

Parameter	Single-family value	Sensitivity range	
		Lower bound	Upper bound
Avg Tenure	0.50	0.50	0.51
Learning per Employee per Year	3.42	1.00	13.69
Avg Knowledge New Hire	22.20	18.30	27.10
A	32.70	31.20	34.40
Alpha	0.28	0.27	0.28
Hiring Adjustment Time	2.54	2.53	2.55
Avg Time to Hire	0.28	0.28	0.28
Avg Time to Complete	0.57	0.57	0.58
Avg Time to Start	0.97	0.95	0.98
Backlog Exponent	2.59	2.56	2.62
Slope	0.32	0.29	0.34
Net Removal Rate	1.50e-03	1.00e-03	2.00e-03
Demand Info Delay	7.91e-03	8.00e-03	2.57e-01
Factor Demand Effect	1.14	1.14	1.15
Demand Effect Exponent	0.09	0.05	0.12
Factor Supply Effect	1.04	1.04	1.04
Supply Effect Exponent	1.11	1.02	1.19
Supply Info Delay	4.79	4.16	5.43
Supply Adjustment Time	3.73	2.87	4.93
Initial Accum Knowledge Factor	82.80	40.30	142.70