

Improving Community Resilience through Post-Disaster Temporary Housing Optimization

VANDERBILT  UNIVERSITY

DANIEL V. PERRUCCI
HIBA BAROUD, PHD

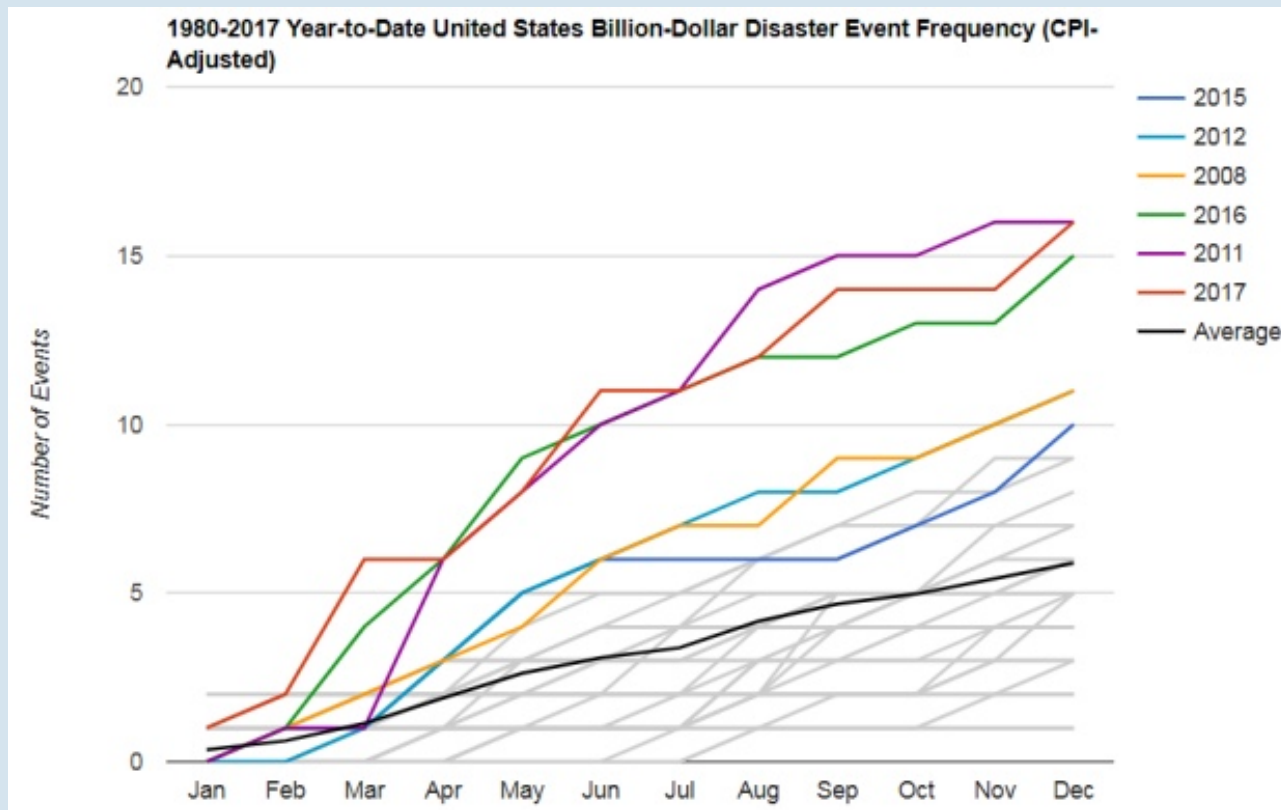
VANDERBILT UNIVERSITY
DEPARTMENT OF CIVIL ENGINEERING

SEPTEMBER 19TH, 2018

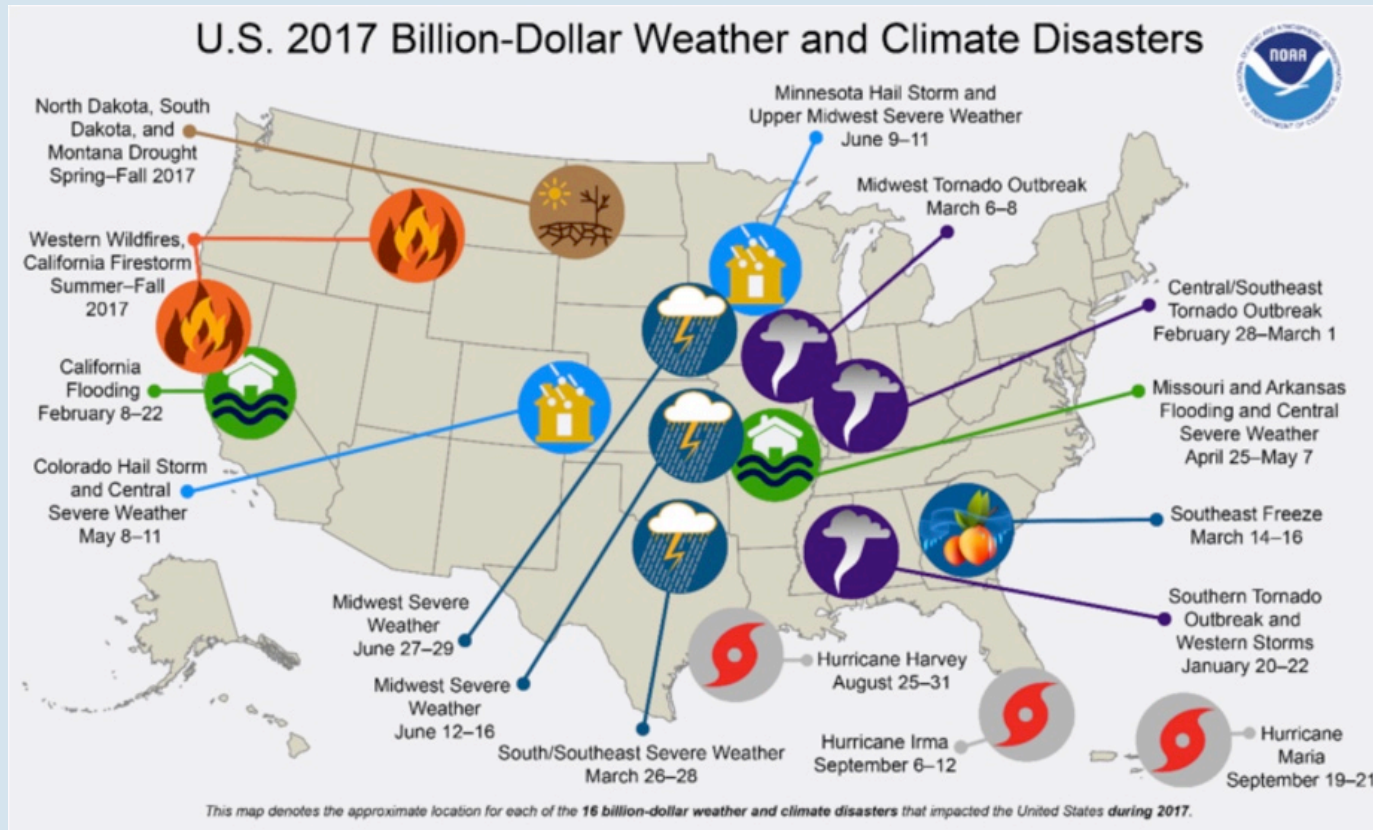
Background



- Recent significant increase in severity and frequency of natural disasters
- Number of post-disaster displaced people following a similar increasing trend.



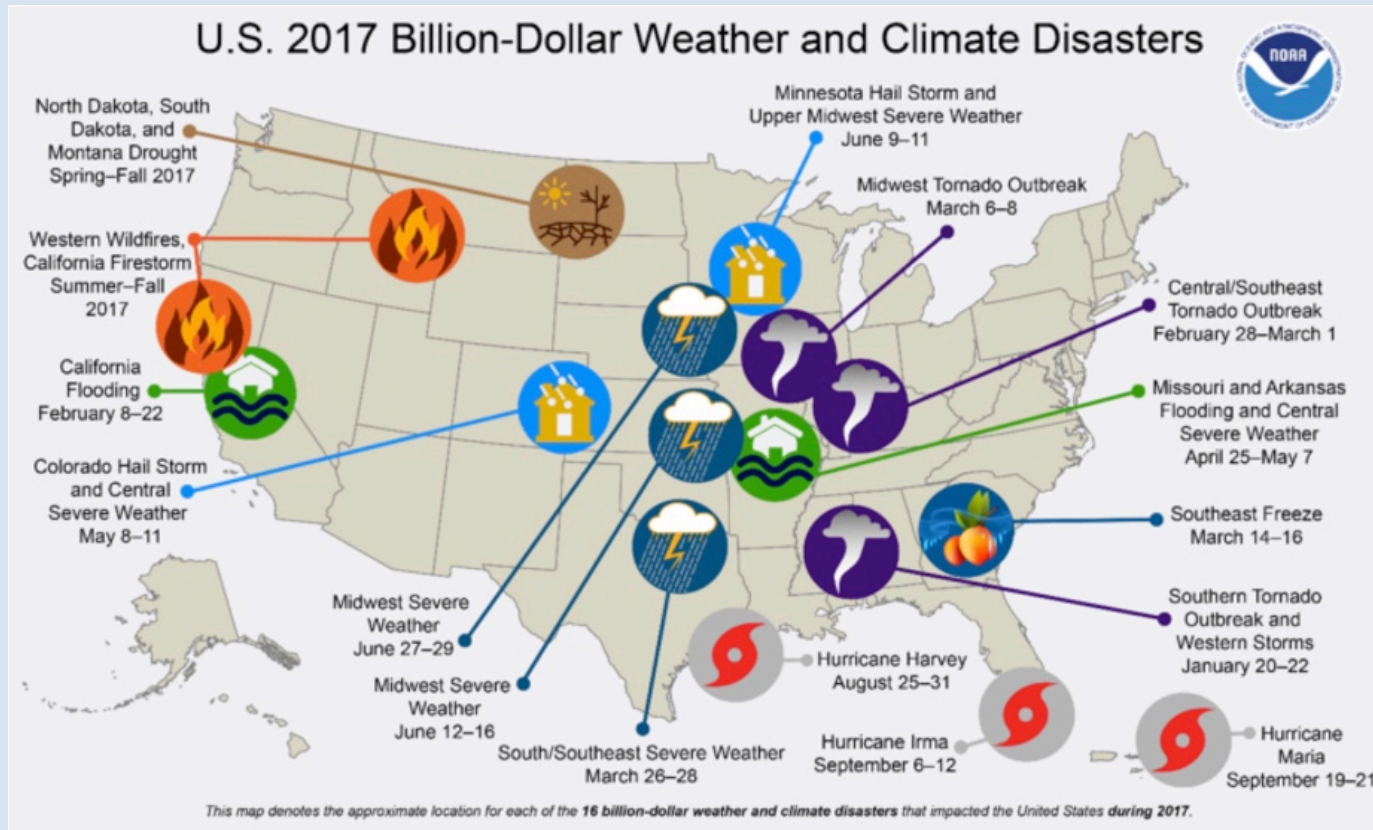
Background



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16 billion dollar disasters in 2017



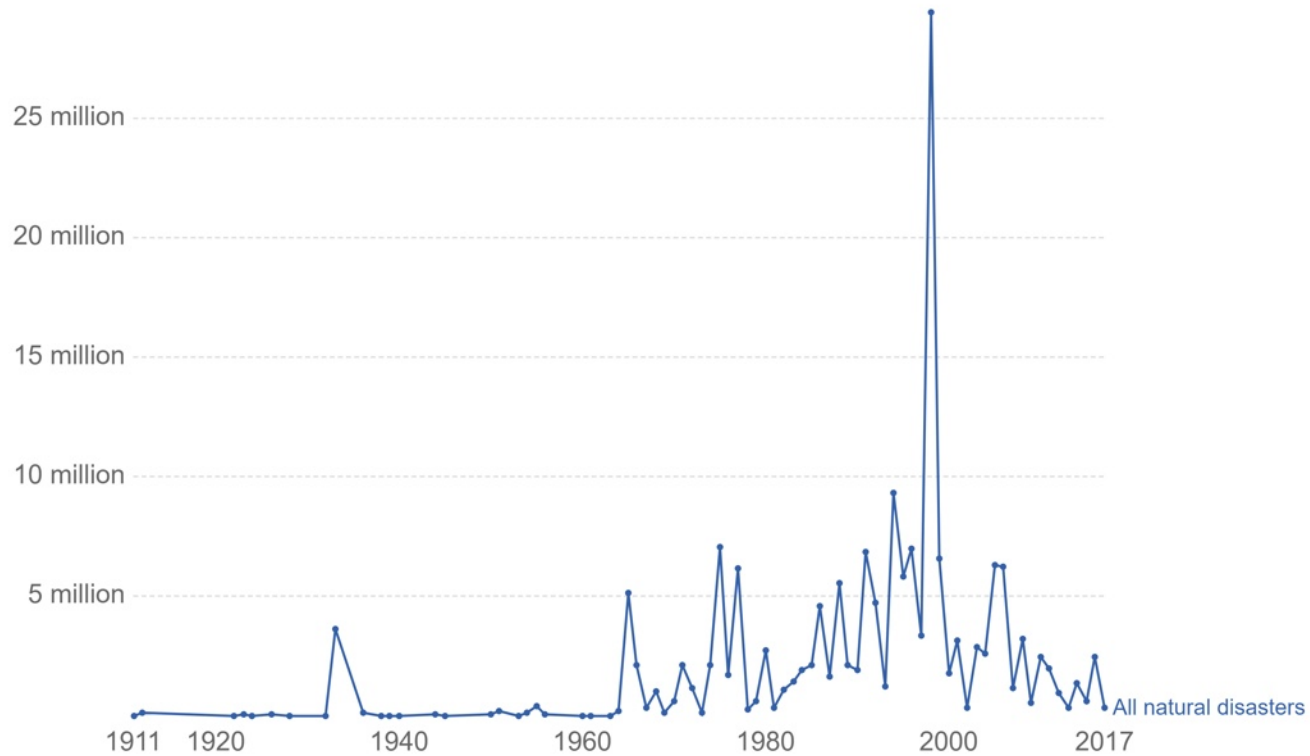
Background



Number left homeless from natural disasters, All natural disasters

Global number of people left homeless from natural disaster events. This is defined as "number of people whose house is destroyed or heavily damaged and therefore need shelter after an event."

Our World
in Data

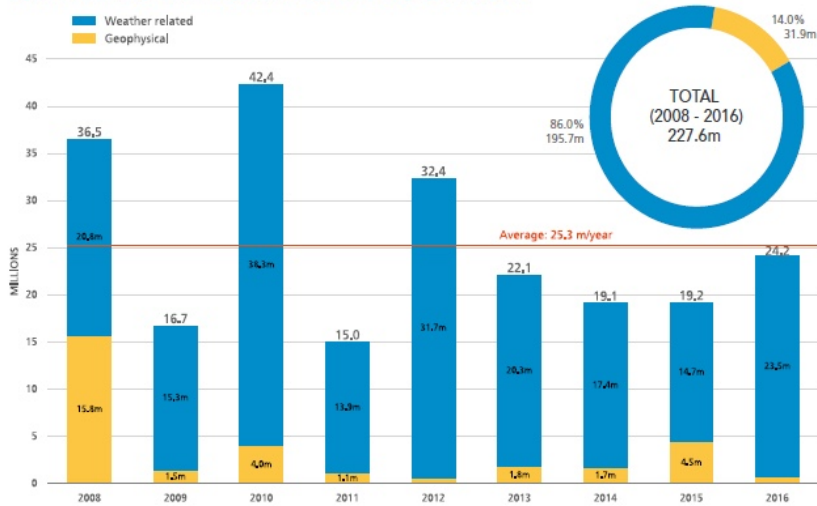


Source: EMDAT (2017): OFDA/CRED International Disaster Database, Université catholique de Louvain – Brussels – Belgium
OurWorldInData.org/natural-catastrophes/ • CC BY-SA

Background



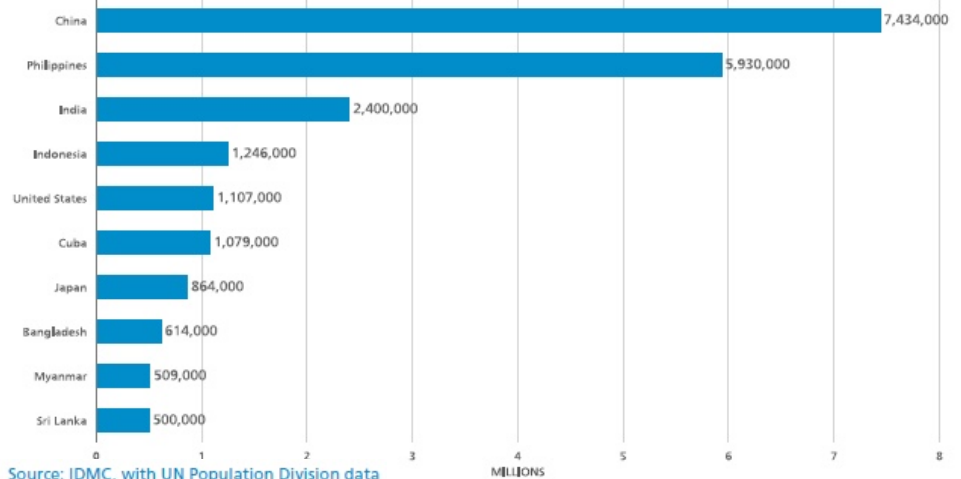
Figure 1.14: New displacements by disasters by hazard category, 2008 to 2016



Source: IDMC

Figure 1.19: Countries with the most new displacements by disasters in 2016

Absolute numbers



Source: IDMC, with UN Population Division data

Background: What is Community Resilience?



Community resilience: The ability of a community to successfully respond to and recover from a disaster.

- A **community's post-disaster resilience** is dependent on the **citizens'** ability to **return** to the devastated area
- For example, Hurricane Katrina's temporary housing locations discouraged the return of residents and hindered the city's ability to recover



Background: What is Temporary Housing?



Table 1: Summary of Utilized Data

Shelter Type	Expected Use Timespan	Examples
Emergency Shelter	1 to 3 Nights	A safe dry location or building
Temporary Shelter	2 to 3 Weeks	Tent or public mass shelter
Temporary Housing	6 Months to 3 Years	Rental houses or prefabricated units
Permanent Housing	-	A new, upgraded or refurbished home



<https://www.manufacturedhomes.com/blog/fema-downplays-manufactured-home-units-hurricane-recovery/>

Introduction



Hurricane Harvey's devastation resulted in prolonged displacement for nearly 40,000 peoples.

- 8,000 occupying all vacant rental options/hotels
- 30,000 in emergency shelters.

The proposed solution for this housing dilemma is to improve community resilience using a **data-driven forecasting and supply chain model**, which accounts for disaster severity and available inventory of manufactured temporary housing units.

Data-Driven Forecasting Model



Consumer Price Index (CPI): “measures the average change over time in prices paid by urban consumers for a market basket of consumer goods or services”

Parameters

CPI_L : *Consumer Price Index-Adjusted Losses*

THU : *Temporary Housing Unit*

$$\text{Average } CPI_L \text{ per } THU(\bar{x}) = \frac{\sum_{i=0}^n \left(\frac{CPI_{Li}}{THU_{req_i}} \right)}{n}$$

n = Number of disaster being considered

$$THU \text{ Forecast} = \frac{CPI_i}{\bar{x}}$$

Historical Temporary Housing Data and Forecast



Table 2: Summary of Utilized Data with Forecasted Demand

Hurricane	Year	Rank	Category	Temp. Housing Units	CPI-Adjusted Losses (in billions)
Katrina, Rita	2005	1	3	+200,000*	\$ 185.2
Harvey	2017	2	4	5,283	\$ 125.0
Ivan, Charley, Frances, Jeanne	2004	3	4	17,000	\$ 71.6
Sandy	2012	4	1	118*	\$ 70.9
Ike	2008	5	2	3,692	\$ 35.1
Wilma	2005	6	3	1,182	\$ 24.5
Irene	2011	7	1	784	\$ 15.1
Mathew	2016	8	4	161	\$ 10.4
* Not considered for this study					

**Hurricane Katrina, Rita and Sandy's THU data were excluded from the study.*

Katrina and Rita excluded because the large temporary housing response skewed the data and was identified as an outlier.

Sandy excluded due to New York's active effort to minimize temporary housing usage.

Validation of Forecasts



Table 3: Validation of Forecasted Demand

Hurricane	Year	Rank	Category	THUs	Forecast THUs	CPI-Adjusted Losses (in billions)
Katrina, Rita	2005	1	3	+200,000	7,827	\$ 185.2
Ivan, Charley, Frances, Jeanne	2004	3	4	17,000	3,026	\$ 71.6
Sandy	2012	4	1	118	2,996	\$ 70.9
Ike	2008	5	2	3,692	1,483	\$ 35.1
Wilma	2005	6	3	1,182	1,035	\$ 24.5
Irene	2011	7	1	784	638	\$ 15.1
Mathew	2016	8	4	161	439	\$ 10.4

The forecasted levels accurately predict the lower adjusted CPI disasters, but become conservative with larger CPI losses.

- Conservative forecast only hinders effect of the supply chain model

Supply Chain Model: The Newsvendor



The newsvendor model:

- Historically used for inventory control
- Maximizes the expected profit or minimizes the expected loss
- Reduces restocking or emergency purchasing delays

J. Wu, J. Li, S. Wang, and T. C. E. Cheng, "A Note on Mean-variance Analysis of the Newsvendor Model with Stockout Cost", Omega, no. 852, pp. 1–15, (2008).

Critical Fractile for Standardized Normal Loss

$$L(Z^*) = \frac{C_u}{C_o + C_u} \quad (1)$$

Optimized Stocking Inventory

$$Q^* = \mu + Z \times \sigma \quad (2)$$

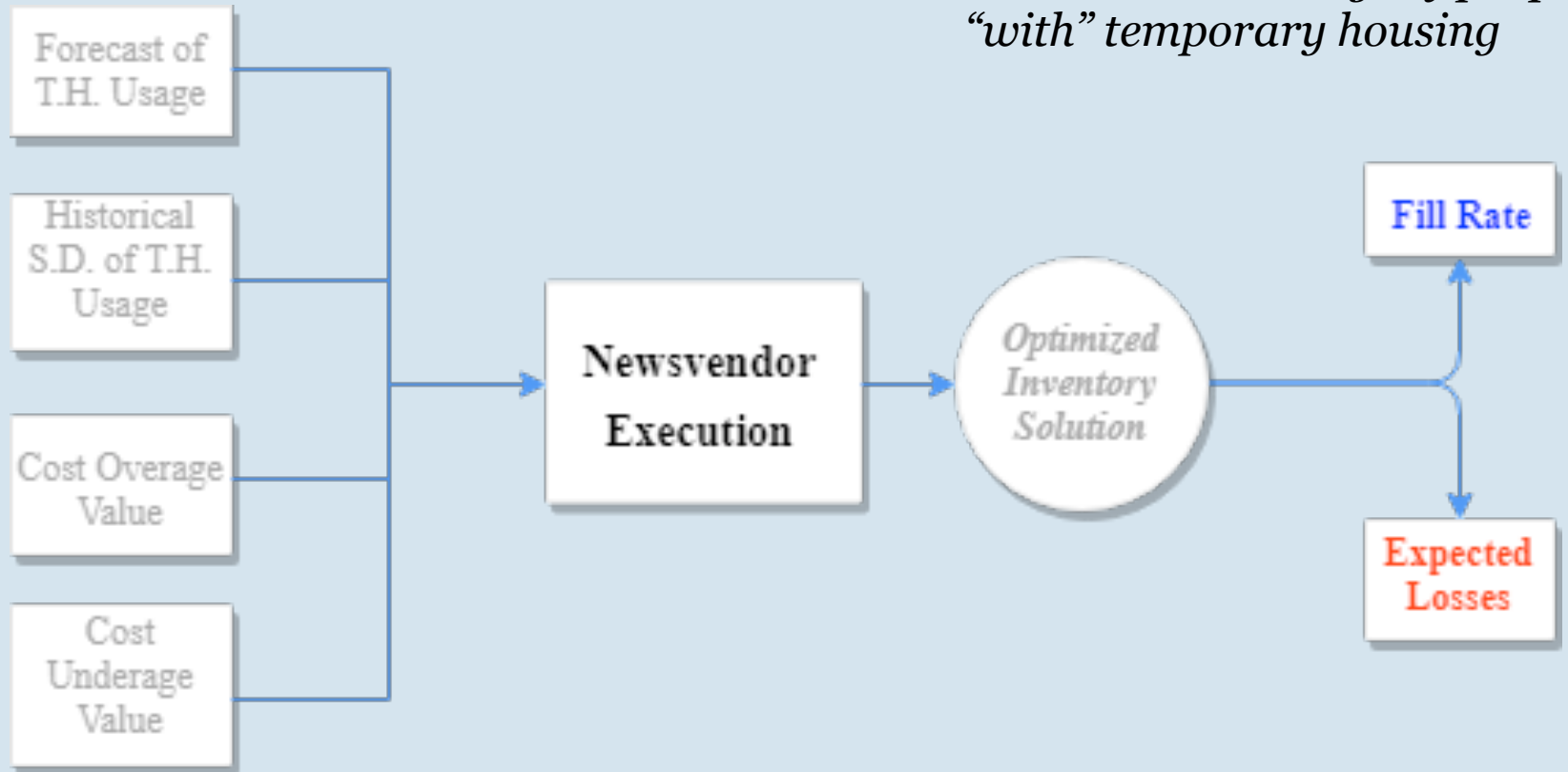
C_u = Cost of one unit too few
 C_o = Cost of one unit too many

Co: \$35,000 Cu: \$90,000

*Values assessed from a FEMA professional and an industry professional

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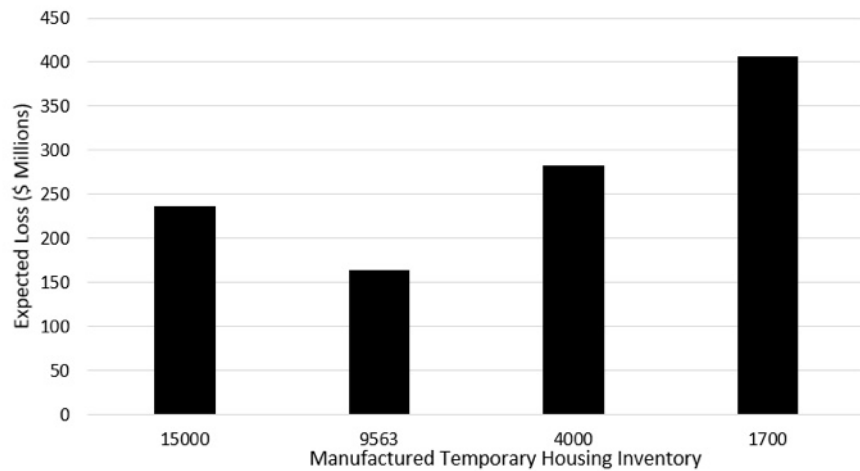
Supply Chain Model: Structure



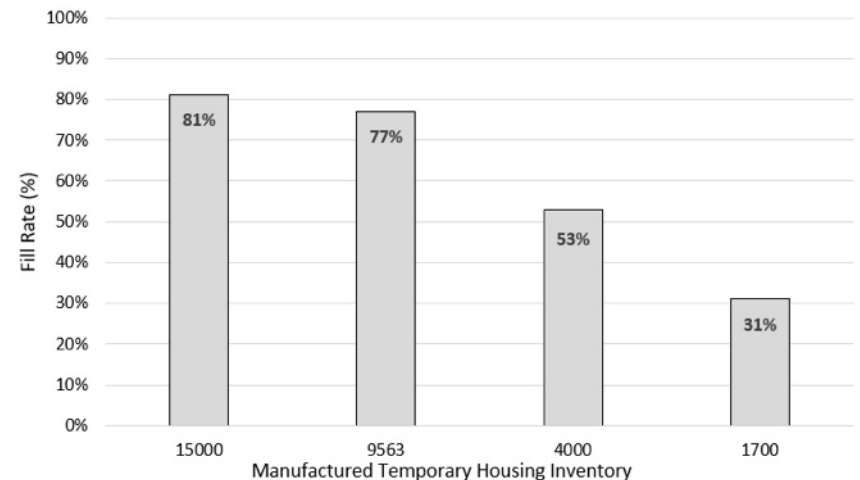
Results: Improved Community Resilience through Optimal Temporary Housing Inventory



Expected Loss Comparison



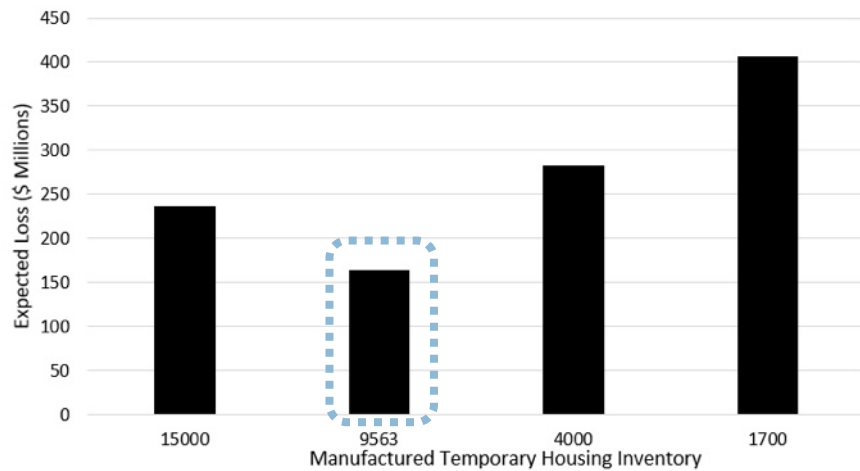
Fill Rate vs. Temporary Housing Inventory



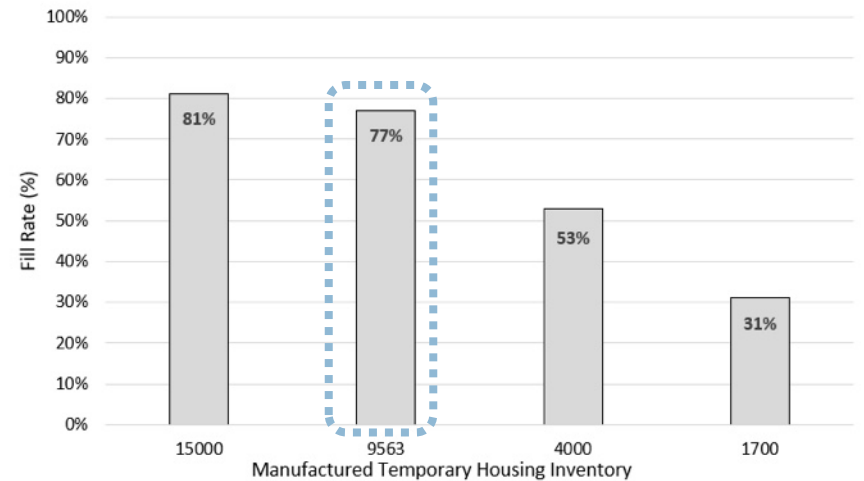
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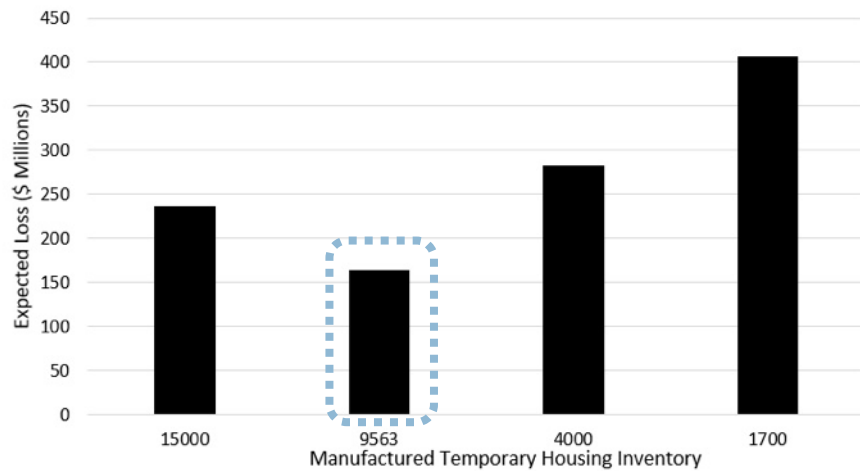
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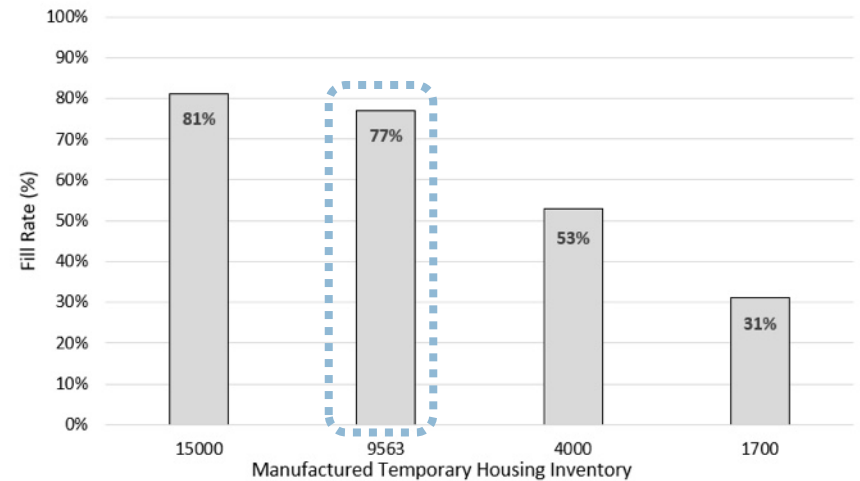
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Fill Rate vs. Temporary Housing Inventory

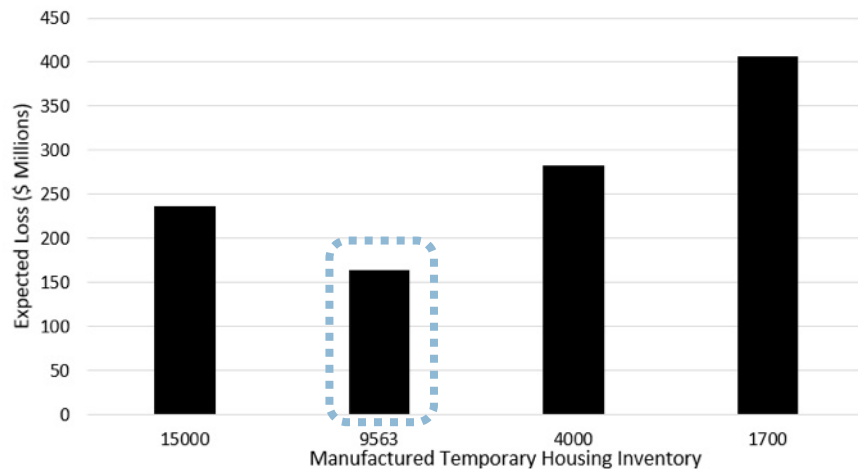


*Fill Rate: Percentage of people
“with” temporary housing*

Results: Improved Community Resilience through Optimal Temporary Housing Inventory

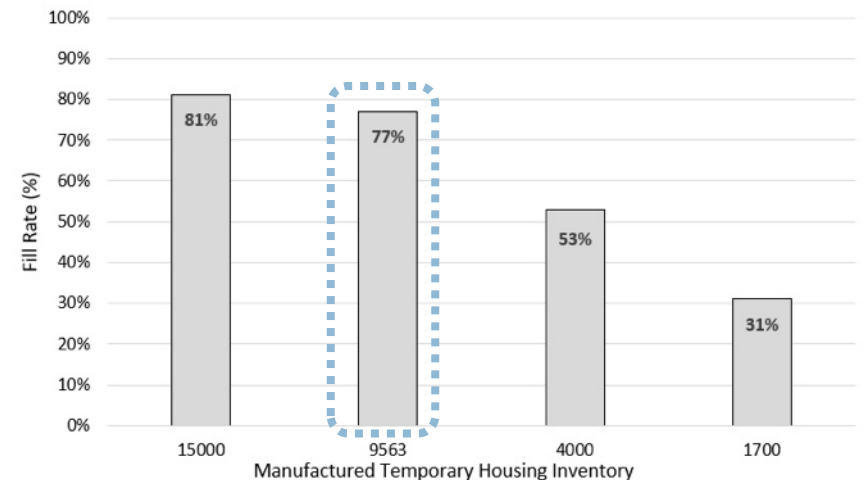


Expected Loss Comparison



*Expected loss for **9,563 THU** is **\$164 million** for Hurricane Harvey*

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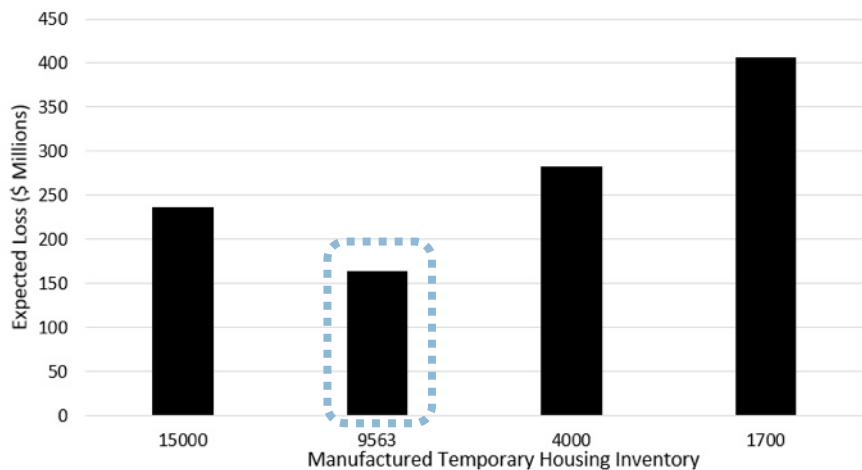


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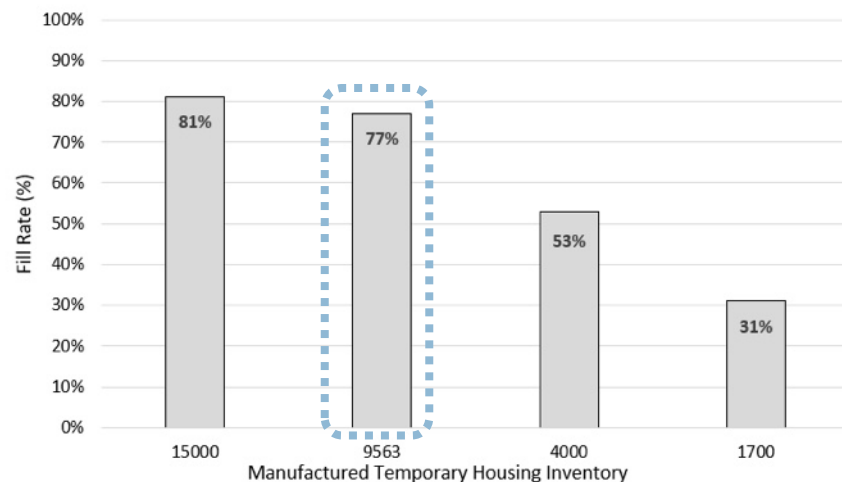


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Fill Rate vs. Temporary Housing Inventory



Fill Rate: Percentage of people “with” temporary housing

FEMA’s THU baseline inventory is 4,000, and it was reported that in actuality have only 1,700.

Conclusion



The data-driven forecasting and supply chain models are **successful** at **improving the community resilience** in post-disaster scenarios.

The newsvendor stocking quantity of **9,563** THU would:

Conclusion



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The newsvendor stocking quantity of **9,563** THU would:

- Provide a predicted 77% fill rate for temporary housing needs.
 - Compared to a fill rate of **53%** and **26%** from FEMA's baseline inventory of 4,000 and the reported actual inventory of 1,700

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- Reduce expected losses by approximately:
 - \$129 million from FEMA's baseline inventory of 4,000 set in 2011
 - \$243 million from the reported actual inventory of 1,700

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The data-driven forecasting and supply chain models are **successful** at **improving the community resilience** in post-disaster scenarios.

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- Reduce expected losses by approximately:
 - \$129 million from FEMA's baseline inventory of 4,000 set in 2011
 - \$243 million from the reported actual inventory of 1,700
- Can be applied to any natural disaster:
 - Hurricane Maria, Florence, etc.

Questions?

