Financial Regulation and AI: A Faustian Bargain?

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February 2026

Abstract

We study whether AI methods applied to large-scale portfolio holdings data can improve financial regulation. We build a state-of-the-art, graph-based deep learning model tailored to security-level data on the holdings of financial intermediaries. The architecture incorporates economic priors and learns latent representations of both assets and investors from the network structure of portfolio positions. Applied to the universe of non-bank financial intermediaries, covering nearly $40 trillion in wealth, the model substantially outperforms existing approaches in out-of-sample forecasts of intermediary trading behavior, including in crisis episodes. Its learned representations capture economically meaningful structure that conventional measures miss: the model has more than ten times the explanatory power for the cross-sectional variation in asset returns during stress events compared to traditional approaches, and it outperforms existing systemic risk metrics at the institution level. The architecture is fully inductive: even when entire asset classes or investors are withheld from training, the model still produces informative forecasts for those unseen entities. We embed our empirical approach into a macroprudential optimal policy framework to formalize why these objects matter for policy and welfare. We show that even in an equilibrium environment subject to the usual Lucas critique, the predictive information from the model improves welfare by sharpening the cross-sectional targeting of policy interventions, and we demonstrate a complementarity between prediction and structural knowledge.

Keywords: Artificial Intelligence, Graph Neural Networks, Holdings Data, Fire Sales, Macroprudential Policy, Asset Pricing, Embeddings, Stress Testing, Deep Learning, Transformers.

JEL Codes: C4, G1, G2.

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We thank Markus Brunnermeier, Hui Chen, Maryam Farboodi, Paul Fontanier, Xavier Gabaix, Stefano Giglio, Tarek Hassan, Arvind Krishnamurthy, Hanno Lustig, Matteo Maggiori, Pablo Ottonello, Markus Pelger, Ashesh Rambachan, Jesse Schreger, Jann Spiess, Stijn Van Nieuwerburgh, and Yuyan Wang for helpful comments. We also thank Oliver Wang and Zhongyu Yin for outstanding research assistance. Financial support from the Stanford GSB Business, Government, and Society (BGS) Initiative is gratefully acknowledged.

1 Introduction

A central task of macroprudential financial regulation is to identify where shocks will be amplified through the financial system and to intervene before the resulting price dislocations become socially costly. The information environment facing regulators has changed sharply: supervisory filings and security-level holdings records now provide granular data on portfolio positions across a large share of the financial system, while high-dimensional predictive methods have become dramatically more capable. This paper shows that deep learning models, when properly designed for the rich cross-section of holdings data now available, can substantially improve the measurement of financial fragility across multiple dimensions relevant for regulation: forecasting institutional trading, explaining crisis-period price dislocations, and measuring systemic selling pressure. We complement our empirical analysis with a macroprudential policy framework that provides one disciplined interpretation of when and why such predictive information can improve the targeting of policy interventions.

Learning effectively from data on institutional portfolios requires building models whose architecture appropriately reflects the structure of the problem, effectively imposing a form of economic regularization. This motivates our focus on architecture design. Fire-sale dynamics which are at the core of financial crises are inherently a networked phenomenon: they propagate through the network of overlapping portfolios that connects investors and assets. For example, a fund forced to liquidate corporate bonds depresses prices for every other intermediary holding those same bonds, potentially triggering further rounds of forced selling. The cross-sectional pattern of who is likely to sell what in a crisis therefore depends on the full high-dimensional structure of portfolio overlaps across the financial system, not merely on the characteristics of individual investors or assets in isolation. Much of the modern deep learning toolkit, including sequence-based architectures that have been recently applied in asset pricing contexts, is designed for sequential or grid-structured inputs such as text and images. Yet in domains where the data has an important network structure, architectures tailored specifically to learn from it have achieved breakthrough performance (Jumper et al. 2021). We therefore design our deep learning approach to explicitly capture and make use of the full network structure of portfolios.

Specifically, we build a *graph transformer*, an attention-augmented graph neural network that learns latent representations of both investors and assets by iteratively propagating information along the holdings network. The architecture incorporates economic priors, for instance by using portfolio exposures as biases in its attention mechanism, so that positions of greater economic importance receive correspondingly greater weight in the information aggregation. We train the graph transformer on quarterly holdings data covering the positions of roughly 37,000 non-bank financial intermediaries in 85,000 assets, totaling nearly $40 trillion in wealth. Our empirical application focuses on non-bank financial intermediaries since they are an increasingly important source of financial fragility, partly as a result of regulatory reform following the Great Financial Crisis. The model takes as input the current cross-section of portfolio holdings and a realized or scenario value of aggregate financial stress, and for each investor-asset pair it produces a forecast of the quantity change in each position. Hence the estimation target is the cross-sectional pattern of trading conditional on the aggregate state, not a forecast of the state itself—a distinction that, as we discuss, is directly relevant for regulatory applications. The primary value of holdings data in our approach therefore lies in predicting which investors will adjust which positions given the prevailing stress level, not in predicting whether a crisis will occur.

We demonstrate the performance of the model in three different but related dimensions that are relevant for risk management and financial regulation. First, under a strict walk-forward out-of-sample evaluation, in which the model is retrained each year and tested on strictly future data, the graph transformer substantially outperforms conventional balance-sheet measures, standard econometric methods, and alternative deep learning benchmarks in predicting financial intermediaries' trading behavior, including through crisis episodes. The model outperforms benchmarks on both the extensive margin (predicting which investor-asset positions are traded) and the intensive margin (how large trades are, conditional on trading). Importantly, we show the model generalizes inductively: even when entire asset classes (e.g., all corporate bonds) or entire sets of investors are withheld from training, it still produces informative forecasts for those unseen entities, confirming that the model learns underlying patterns and mechanisms of trading behavior that generalize beyond the specific sample seen during training.

Second, and of particular interest from an asset pricing perspective, the model's learned representations (embeddings) of assets and investors explain the cross-section of asset price dislocations during stress episodes, despite the model never having been trained on price or returns data. Traditional approaches to explaining crisis-period asset returns rely on collapsing the high-dimensional holdings data into a few low-dimensional summary statistics motivated by economic theory. We show that the graph transformer's embeddings deliver more than ten times the incremental explanatory power of these traditional summaries for the cross-section of bond returns in stress periods: 18 percentage points of incremental adjusted R-squared beyond standard asset characteristics, compared to roughly 1 percentage point from the best existing low-dimensional approaches. Intuitively, unlike traditional approaches, the model captures the entirety of the high-dimensional information in the data that is relevant for trading behavior and fire sale dynamics: for example, which positions are most crowded, which specific institutions are most exposed to funding instability, or where forced selling is likely to concentrate.

Third, as a systemic risk metric, the model's predicted selling intensity outperforms existing institution-level measures—including ΔCoVaR, fund outflows, trailing portfolio returns, and portfolio concentration—by a wide margin in the non-bank setting we study. We also construct prediction intervals around the model's forecasts using conformal methods, demonstrating that the uncertainty around these predictions can be quantified in a distribution-free manner across both calm and stress market regimes. These results suggest that the architecture recovers economically meaningful heterogeneity that conventional summaries miss. When embedded in the policy framework, this heterogeneity translates into better-targeted intervention and higher welfare.

Two additional properties of our deep learning architecture make it particularly well-suited to our setting. First, the model is permutation-invariant: predictions do not depend on the arbitrary ordering of investors or assets. This is a key distinction from sequence-based architectures such as the text transformers that underpin modern large language models, in which the order of tokens is essential to their contextual meaning. In our setting, permutation invariance respects a fundamental symmetry of the problem. Second, the graph transformer is inductive: all model parameters are fully shared across nodes, allowing the model to generalize to new investors or assets without retraining, as we verify empirically in practice. This is not merely a convenience but a practical necessity for regulatory deployment, where new entities continuously enter and exit the data. Parameter sharing also enforces a strong form of regularization, leading to good generalization out of sample. Together, these properties lead to highly sample-efficient learning that distinguishes graph-based architectures from alternatives that treat the holdings matrix as an unstructured grid or sequence.

While the empirical objects that we study are of direct, independent interest for financial stability monitoring and macroprudential surveillance, we also develop a complementary theoretical framework that offers one disciplined interpretation of the policy and welfare value of these empirical objects. In particular, the theory lets us address the Lucas (1976) critique, a natural concern with deploying any reduced-form predictive model for policy: the model might forecast distress accurately, but the relationships it learns need not be invariant to the regulation itself. We study this problem in a tractable equilibrium model featuring fire-sale externalities, in which the regulator has imperfect information about the state and chooses a model to inform policy intervention. We characterize the regulator's optimal intervention and show that it decomposes into two inputs. The first is a set of structural elasticities: the causal impact of the regulator's policy instruments on equilibrium liquidation prices. The second is a set of cross-sectional targeting statistics: the forecasted pattern of forced selling across investors and assets that would prevail absent intervention (matching the empirical focus on trading behavior conditional on the aggregate state). The key implication is that a purely predictive model—i.e., one that is uninformative about policy counterfactuals—can improve welfare, provided it sharpens the regulator's forecast of these targeting statistics and the regulator has prior knowledge of the relevant structural elasticities.

We show that under certain conditions on the information structure, the structural loadings that translate portfolios and policy wedges into equilibrium outcomes are invariant to the regulator's model choice, even though intermediaries' ex ante portfolio decisions respond endogenously to the anticipated intervention, making the use of a predictive model robust to the Lucas critique. Intuitively, the robustness comes from the fact that in this framework, predictive models are not used for estimating policy counterfactuals, but simply to improve the cross-sectional targeting of the policy. The theory yields a complementarity result: predictive accuracy is most valuable precisely on the margins where the regulator's causal knowledge is strongest. It also shows that a weighted predictive R-squared, where the weights reflect the causal leverage of the policy, is a sufficient statistic for the welfare gains from a given predictive model, providing a direct bridge between out-of-sample forecast accuracy and the value of the model for regulation. We further study the feedback of model choice on ex ante portfolio decisions, characterize optimal ex ante regulation, and extend the analysis to subsidy-based (bailout) interventions.

The broader contribution of the paper is to clarify the role of prediction in macro-policy problems. In policy environments with high-dimensional state spaces, reduced-form prediction can be valuable even when it is not a substitute for structural modeling: its role is to estimate the sufficient statistics that structural policy rules require for accurate targeting. Structural models remain necessary for disciplined counterfactuals and welfare analysis, while predictive models are valuable because they recover heterogeneity that is difficult to capture with structure alone. In this sense, the paper speaks both to macroprudential regulation and to a broader class of economic policy problems in which governments observe increasingly rich data but still need structurally disciplined rules for intervention.

Related Literature. Our analysis relates to several areas of the literature. First, we connect to the literature on applications of machine learning and deep learning to finance. Gabaix, Koijen, Richmond and Yogo (2024) use holdings data together with a variety of deep learning sequence models (e.g., Word2Vec and BERT) and recommender systems to estimate asset embeddings, and Gabaix, Koijen, Richmond and Yogo (2025) apply these to explain variation and volatility in credit spreads. Chen, Cheng, Liu and Tang (2023) study transfer learning problems to bridge structural and machine learning models in asset pricing. Gu, Kelly and Xiu (2020, 2021), Kozak, Nagel and Santosh (2020), Nagel (2021), and Bryzgalova, DeMiguel, Li and Pelger (2023) apply machine learning techniques to the canonical empirical asset pricing problem of valuation in the cross-section of assets. Similarly, Chen, Pelger and Zhu (2024) introduce a deep learning architecture for modeling stock returns. Giglio, Kelly and Xiu (2022) review the intersection of empirical asset pricing and machine learning. Dolphin, Smyth and Dong (2022) and Sarkar (2025) also construct asset embeddings, respectively from return data and textual sources. Methodologically, our paper employs graph neural network architectures (Scarselli, Gori, Tsoi, Hagenbuchner and Monfardini 2008; Hamilton, Ying and Leskovec 2017; Xu, Hu, Leskovec and Jegelka 2018; Wu, Pan, Chen, Long, Zhang and Yu 2020) to learn representations from the relational structure of asset holdings data.[1]

Our applications of machine learning models for financial regulation relate to a longstanding debate, from Koopmans (1947) to Friedman (1953) and Lucas (1976), about whether predictive relationships that are not themselves structural can inform policy. We show that sufficiently capable predictive models can have a role in the macro-regulatory toolbox, not as substitutes for structural models, but as complements that recover high-dimensional targeting statistics while structure disciplines counterfactuals.

[1]See also Elliott, Golub and Jackson (2014) and Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) for theory highlighting the importance of the network structure of positions for financial stability.

Second, we connect to the literature on fire sales, and macroprudential regulation and ex-post interventions. Theoretical contributions include Bernanke and Gertler (1986), Williamson (1988), Kiyotaki and Moore (1997), Caballero and Krishnamurthy (2001), Lorenzoni (2008), Bianchi (2011, 2016), Stein (2012), Farhi and Werning (2016), Chari and Kehoe (2016), Bianchi and Mendoza (2018), Dávila and Korinek (2017), and Clayton and Schaab (2022, 2025). On the empirical side, prior work has focused on particular variables to explain and predict the occurrence and magnitude of fire sales, such as leverage and maturity mismatches (Fisher 1933; Kindleberger and Aliber 1978; Brunnermeier and Oehmke 2013; Schularick and Taylor 2012; Adrian and Shin 2014; Adrian and Brunnermeier 2016; Acharya, Pedersen, Philippon and Richardson 2017; Krishnamurthy and Muir 2025) as well as investor composition (Brainard and Tobin 1968; Coval and Stafford 2007; Haddad, Moreira and Muir 2021; Coppola 2025; Fang, Hardy and Lewis 2025): the empirical contribution of this paper asks whether there is additional value from a more agnostic approach that does not impose an ex-ante focus on particular dimensions of the data.

Third, we relate to literature studying the deployment of machine learning and large-scale data for economic analysis and policy problems more broadly, including Einav and Levin (2014b,a), Kleinberg, Ludwig, Mullainathan and Obermeyer (2015), Athey (2017, 2018), Mullainathan and Spiess (2017), Kleinberg, Lakkaraju, Leskovec, Ludwig and Mullainathan (2018), Athey and Imbens (2019), Gillis and Spiess (2019), Farboodi and Veldkamp (2020), and Athey and Wager (2021). Relatedly, a recent literature in macroeconomics has highlighted how empirically identified causal effect estimates can be used to inform policy (Nakamura and Steinsson 2018, McKay and Wolf 2023). The question of how non-policy invariant relationships should be exploited by regulators also has earlier conceptual parallels, for instance by Barro and Gordon (1983) in the context of the Phillips curve. The model and information design aspect of our theoretical approach connects to work on stress testing (Shapiro and Skeie 2015; Faria-e Castro, Martinez and Philippon 2017; Goldstein and Leitner 2018; Leitner and Williams 2023; Orlov, Zryumov and Skrzypacz 2023; Parlatore and Philippon 2025).

2 The Regulator's Problem: Conceptual Framework

This section previews the key theoretical ideas that provide an interpretive framework for our empirical results. The full formal theory is presented in Section 5. Although the empirical objects we study are of broad independent interest, the theory provides one disciplined way to think about their welfare and policy value.

We consider a regulator who oversees intermediaries that may be forced to sell assets to second-best users, depressing prices below fundamentals. The regulator can intervene to disincentivize selling in markets where fire-sale externalities are most severe, but faces uncertainty about the state realization and must rely on a model to form beliefs before choosing how to intervene. The regulator's core question is where to intervene and by how much. Fire-sale externalities vary across markets: a dollar of forced selling in an illiquid corporate bond market may depress prices far more than the same selling in a liquid government bond market. So the regulator needs to know both which markets are under the most selling pressure and how its instruments translate into price changes in those markets. These are two different kinds of information. We formalize this distinction by showing that the regulator's optimal intervention decomposes into two inputs (established formally in Proposition 1, Corollary 1):

$$\text{Optimal intervention} \ = \ f\Bigg(\underbrace{\text{Structural elasticities}}_{\text{Causal impact of policy on prices}} \ , \ \underbrace{\text{Cross-sectional targeting statistics}}_{\text{Predicted pattern of forced selling}} \Bigg). \tag{1}$$

The structural elasticities capture the causal channel: how the regulator's instruments change equilibrium selling, and how those changes move market-clearing prices. These depend on the depth of secondary markets, the binding constraints facing intermediaries, and the structure of demand from arbitrageurs. The targeting statistics capture the predictive channel: the cross-sectional pattern of forced selling across investors and assets that would prevail absent intervention.

The key insight is that a purely predictive model—one that is entirely uninformative about structural elasticities—can nonetheless improve welfare. The social benefit of intervening on any margin is proportional to the amount of forced selling on that margin, because that determines the fire-sale price distortion the intervention can correct. A model that accurately forecasts where selling will concentrate therefore allows the regulator to target its intervention more precisely, even if the model says nothing about how intervention changes outcomes. This interpretation also clarifies why the natural empirical task is to predict the cross-sectional pattern of investor-level trading conditional on the aggregate state. This is the estimation target of the graph transformer we introduce in Section 3.

This complementarity between prediction and structure can be made precise. We show that the welfare gain from a predictive model is proportional to a weighted out-of-sample R^2 in this predictive task (Corollary 2), where assets for which the regulator's instruments have a larger causal effect on prices receive a larger weight. This provides a direct bridge between the out-of-sample predictive accuracy we measure empirically and the welfare value of a model, and it shows that predictive accuracy is most valuable precisely on the margins where the regulator has most confidence in the structural model of the economy.

Finally, because the predictive model forecasts only the targeting statistics and not the causal effect of intervention, it is robust to the Lucas critique. Under the information structure of our model, the structural loadings that translate policy wedges into equilibrium price changes are invariant to the regulator's model choice. Intermediaries' ex-ante portfolios respond endogenously to the expected intervention, but the mapping from portfolios and wedges to outcomes does not change with the model; only the inputs to that mapping do.

3 Structure-Aware Deep Learning for Holdings Data

We now introduce our deep learning architecture tailored to holdings data. Successful deep learning architectures exploit the particular structure of the data they model: for example, convolutional networks for grid-structured data and text transformers for sequences. Financial holdings data does not fit neatly into either category. Instead, its defining feature is rich *relational structure*: the data naturally represents a graph connecting investors and assets, with the information relevant to the learning task contained in the graph's edges, i.e. the positions connecting investors to assets.

Graph neural networks (GNNs) are a class of deep learning models that specifically models and exploits relational structure in the data (Scarselli et al. 2008; Hamilton et al. 2017; Wu et al. 2020). By iteratively propagating and aggregating information along the edges that connect graph nodes (in this case, assets and investors), GNNs learn embeddings for each node in the graph—i.e., representations of the nodes in a latent vector space that effectively capture the characteristics relevant to the tasks the model is trained against. In practice, in our implementation an investor's embedding evolves based on the embeddings of the assets they hold, and those asset embeddings, in turn, adjust in light of the embeddings of the investors that include them. Through iterated rounds of this network-aggregation mechanism (also known as *message passing*), information flows along the network of positions, allowing the model to learn explicitly from the relational structure of the holdings data.

GNNs have achieved strong empirical results in domains where relational structure is paramount, including protein structure prediction (Jumper et al. 2021), traffic forecasting (Derrow-Pinion et al. 2021), and drug discovery (Jiang et al. 2021). While these domains benefit from larger datasets and more stable generating processes than financial markets, the architectural principle—that learning directly from relational structure improves prediction when the data is naturally graph-structured—transfers to the holdings setting, as our empirical results confirm.

In the context of asset holdings data, GNNs have two key properties that other deep architectures lack: permutation invariance and inductive learning. First, the models are *permutation invariant*, meaning that the learning process and estimation results do not depend on any arbitrary relabeling or reshuffling of investor and asset identifiers. The architecture attains permutation invariance because aggregation operates over unordered sets of neighbors, and by doing so they respect a fundamental symmetry of the problem.

Second, the GNN architecture features *inductive learning*. Crucially, all of the model's parameters are shared, in the sense that there are no parameters specific to particular assets or investors. Therefore the same learned representation rules apply across all nodes and edges: given a graph $\mathcal{G}$, regardless of the number and identity of the nodes, the trained GNN architecture is able to construct asset and investor embeddings simply from the graph structure and the node characteristics. Inductive generalization thus follows naturally from parameter sharing: the model can immediately generate embeddings and forecasts for new, unseen investors or assets without any retraining. This feature is not only valuable for real-time regulatory applications, but also it enforces a strong form of regularization upon the model, preventing overfitting of the training data and leading to good generalization to unseen, out-of-sample data.

This combination of relational representation learning, proven empirical performance, permutation invariance, and inductive design makes GNNs a particularly well suited deep learning architecture for the holdings data setting and for macroprudential applications. Our specific implementation is a graph transformer: an attention-augmented GNN, which incorporates an attention mechanism in the basic architecture, as we discuss below.

Estimation Objective. The goal of the empirical model is to learn how each investor in the financial system trades each asset in response to the prevailing state of the world. This cross-sectional prediction task is of direct empirical interest for financial stability monitoring, stress testing, and systemic risk measurement. As we discuss in Section 5, it also has a natural interpretation in terms of the targeting statistics relevant for optimal policy.

Formally, let $\mathcal{G}_t$ denote the observed holdings data at time t: this is the full cross-section of who holds what, and how much, at the end of period t. For the purposes of our deep learning architecture, we model $\mathcal{G}_t$ as a graph connecting investors to assets via their positions, a data structure that we formally specify below. We also let ζ_{t+1} be a scalar summary of the aggregate state that prevails during period $t+1$: this is a single number that summarizes the extent to which the period represents a stress regime or a calm regime. In our implementation, we use the Financial Stress Index (FSI) published by the St. Louis Fed as our aggregate state summary ζ_{t+1}.

We distinguish between market-value positions $w_{ia,t}$ and notional-quantity positions $q_{ia,t}$. The position $w_{ia,t}$ corresponds to the market value of the holdings of investor i in asset a at each time period t, while $q_{ia,t}$ denotes the notional quantity (shares for equity securities and par value for bonds) of asset a held by investor i. We are interested in learning a model for trading behavior, and hence for each investor-asset pair (i, a), we define the trade outcomes

$$y_{ia,t+1} = \log\left(\frac{q_{ia,t+1}}{q_{ia,t}}\right), \tag{2}$$

which capture the pure quantity change in investor i's position in asset a between the end of period t and the end of period $t+1$.[2] The central estimation target is the conditional trading response

[2]The log transformation places buys and sells on a symmetric scale: doubling a position and halving it yield targets of equal magnitude with opposite sign. In our implementation, we clip the values of $y_{ia,t+1}$ to the range $[-5, 5]$ to limit the influence of extreme outliers from very small initial positions. The target $y_{ia,t+1}$ is only defined for continuing positions with $q_{ia,t} > 0$: new entries ($q_{ia,t} = 0$) are excluded from model training and evaluation.

function:

$$\hat{y}_{ia,t+1} = \hat{\mathbb{E}}\left[\underbrace{\log\left(\frac{q_{ia,t+1}}{q_{ia,t}}\right)}_{\text{Trade from } t \text{ to } t+1} \;\middle|\; \underbrace{\mathcal{G}_t}_{\text{Positions at } t}, \underbrace{\zeta_{t+1}}_{\text{Aggregate state}} \right] \quad \text{for all } (i,a). \tag{3}$$

That is, for each investor-asset pair (i, a), the model takes as inputs the current cross-section of portfolio positions $\mathcal{G}_t$ and a realized (or scenario) value of aggregate financial stress ζ_{t+1}, and produces a (conditional) forecast of the quantity change in each position over the subsequent period. These conditional expectations can be understood as reaction functions: given the configuration of the financial system at time t, they describe how each investor adjusts each position conditionally on a given level of aggregate financial stress.

Several features of the conditioning in equation (3) are worth emphasizing. First, the model does not forecast the aggregate state ζ_{t+1} itself. Rather, it takes ζ_{t+1} as given—either as a real-time observable that the regulator can measure when designing the intervention, or as a hypothetical stress scenario that the regulator can vary—and forecasts the cross-sectional pattern of trading responses conditional on that state. This conditioning structure is also natural from a regulatory perspective: a supervisor designing an intervention during a stress episode can observe the prevailing level of financial stress but needs to forecast how different institutions will respond to it. Second, the information set $\mathcal{G}_t$ consists entirely of time-t observables (current portfolio positions as well as the corresponding investor and asset characteristics) while the prediction target $y_{ia,t+1}$ is a forward-looking quantity that will be realized in the future.

We target the full cross-section of trading behavior $\{y_{ia,t+1}\}$ rather than crisis-period forced liquidations directly, for two reasons. First, forced liquidations are not directly observed: realized trades reflect the superposition of many motives, and isolating forced selling necessarily requires additional assumptions. Second, fire sale episodes are rare, so a model targeting crisis liquidations directly would face a severe small-sample problem; training on the broader task of predicting all trading behavior exploits far more data and learns general patterns of portfolio adjustment that are informative about the specific adjustments constituting fire sales. Our approach instead learns general-purpose representations of investors and assets from the full distribution of trading behavior, and we then verify empirically that these representations are informative about fire sale dynamics by showing that the learned embeddings explain the cross-section of asset price dislocations during market stress episodes (as shown in Section 4). We note that mapping predicted trades to aggregate forced liquidation measures would require an additional modeling step separating forced from voluntary trades, which we do not undertake here.

Core Architecture Specification. We now formally specify the GNN architecture used to estimate the conditional trading response functions in equation (3). We model holdings data using a graph data structure. The holdings graph $\mathcal{G}_t$ is bipartite—it has two distinct types of nodes, and edges only connect nodes of different types—with investors connecting to assets via position edges. Formally, at each time t, the holdings graph is $\mathcal{G}_t = (\mathcal{I}_t, \mathcal{A}_t, \mathcal{E}_t)$, where $\mathcal{I}_t = \{1, \dots, I_t\}$ is the set of investors, $\mathcal{A}_t = \{1, \dots, N_t\}$ is the set of assets, and $\mathcal{E}_t$ is the set of edges (i.e., positions). Whenever investor i holds asset a at time t, we write $w_{ia,t}$ for the market-value size of the position and $q_{ia,t}$ for the notional-quantity position, so that $(i, a, w_{ia,t}, q_{ia,t}) \in \mathcal{E}_t$.[3] We write $\mathcal{V}_t = \mathcal{I}_t \cup \mathcal{A}_t$ as the set of all nodes, both assets and investors, and let $N_t(v)$ be the neighborhood set for a given node v—the set of all nodes connected to v at time t: for assets, $N_t(v)$ corresponds to the investors holding the asset, while for investors this corresponds to the set of assets in the investor's portfolio.

Each node $v \in \mathcal{V}_t$ also has an associated set of characteristics $x_{v,t}$. The characteristics can be either numerical (e.g., the total amount outstanding of a given security) or categorical (e.g., the type of institutional investor). For categorical features, these are pre-embedded to a vector space of dimension d_c using maps that are learned jointly with the rest of the model's parameters. The node characteristics vector $x_{v,t}$ concatenates over all individual features, both scalar-valued ones and vector-valued categorical ones.

The model learns node embeddings (both asset embeddings and investor embeddings) at various hierarchical levels of information aggregation. The first-level embeddings, which we denote as $h^{(0)}_{v,t}$, are obtained simply by embedding the node characteristics vectors $x_{v,t}$ into a d_h–dimensional hidden space via a learnable map ϕ consisting of a feed-forward multilayer perceptron (MLP) layer set:

$$h^{(0)}_{v,t} \; = \; \phi(x_{v,t})\,. \tag{4}$$

Next, the architecture passes these layer-zero node embeddings through several successive layers of message passing which aggregate information over the graph: this message passing stage is the core of the GNN model and is what allows the model to learn from the data's relational structure. To increase the expressivity and learning capability of the model, we integrate attention mechanisms in each of the GNN message passing layers, which allow the architecture to learn from the data which positions should be given more or less weight in any given information aggregation steps. Attention is computed using scaled dot-product (transformer-style) queries and keys (Vaswani et al. 2017).

We perform L distinct layers of message passing. The message passing at layer ℓ unfolds in several distinct steps. First, the prior-layer node embeddings are passed through feed-forward network layers $M^{(\ell)} : \mathbb{R}^{d_h} \to \mathbb{R}^{d_h}$ to construct *node messages*:[4]

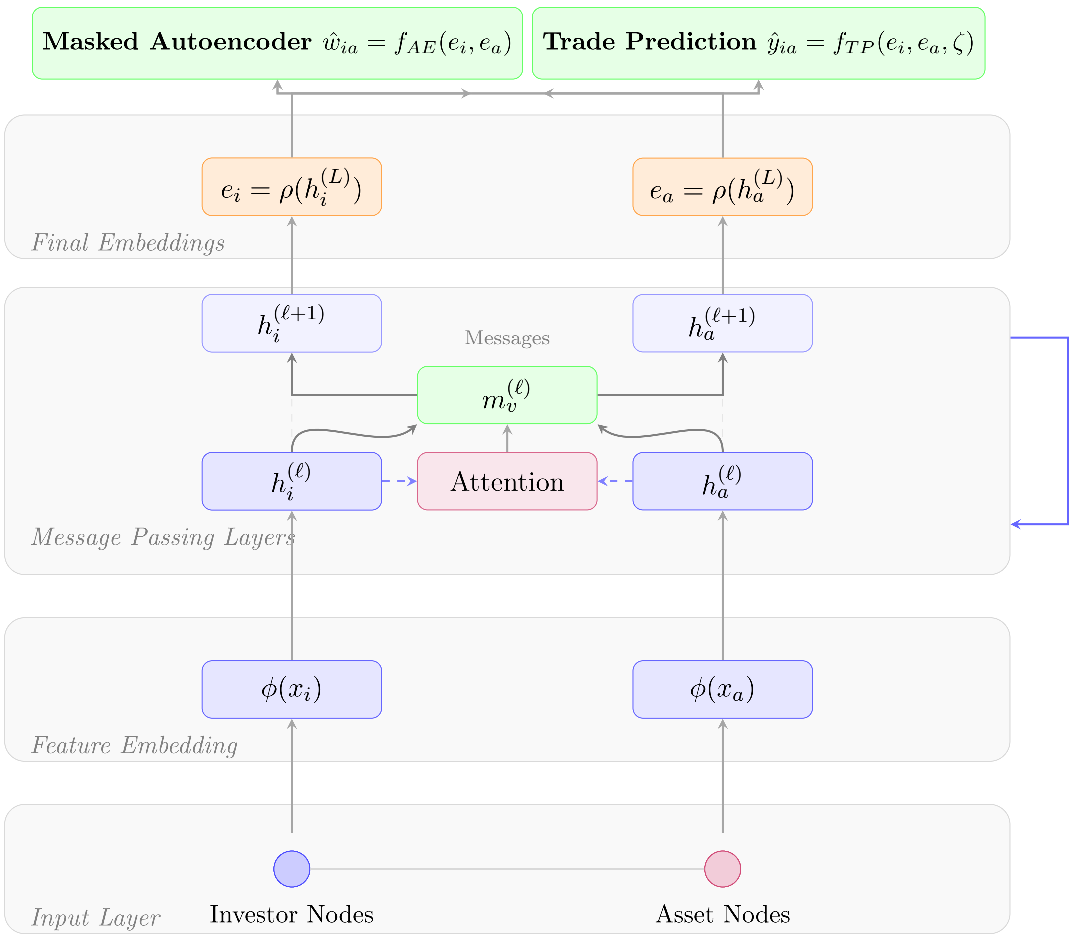
$$M^{\ell}_{v,t} = M^{(\ell)}(h^{(\ell-1)}_{v,t}). \tag{5}$$

Next, the attention mechanism computes aggregation weights that dictate how the individual node messages will be weighted when passing information over the graph. We incorporate the economic

[3] The positions can alternatively be written as $w_{ai,t} = w_{ia,t}$ and $q_{ai,t} = q_{ia,t}$. We allow for both notations so as to keep the rest of the formal architecture specification symmetric.

[4] All feed-forward layers in our architecture use GELU non-linearities (Hendrycks and Gimpel 2016). These help avoid dead gradients during training.

Figure 1: **Model architecture**



Notes: We visualize the architecture of our graph transformer model diagrammatically.

importance of each position using a normalized edge exposure $\tilde{w}_{vu,t} \in (0, 1]$, which is constructed from the raw market-value position $w_{vu,t}$ by normalizing within each node's neighborhood:

$$\tilde{w}_{vu,t} \;=\; \frac{w_{vu,t}}{\sum_{k \in \mathcal{N}_t(v)} w_{vk,t}} \qquad \text{for } u \in \mathcal{N}_t(v). \tag{6}$$

This normalization ensures that edge exposures are comparable across nodes and prevents extremely large raw positions from dominating the attention weights.

The architecture uses S_A independent attention heads with scaled dot-product (transformer-style) queries and keys (Vaswani et al. 2017). For each head, learnable projection matrices produce query, key, and value representations from the node embeddings. The attention weights incorporate the normalized edge exposure $\tilde{w}_{vu,t}$ as an additive log-bias, ensuring that positions of greater economic importance receive correspondingly greater weight in the information aggregation. The attention-weighted messages from each head are then averaged to produce the aggregated message $m^{(\ell)}_{v,t}$ for each node. Full details of the attention computation are provided in Appendix B.

The node embeddings at the next hierarchical stage ℓ are then updated using another feed-forward layer $U^{(\ell)} : \mathbb{R}^{2d_h} \to \mathbb{R}^{d_h}$ which maps the current embeddings and the current aggregated messages into the next-stage representations:

$$h^{(\ell)}_{v,t} = U^{(\ell)}(h^{(\ell-1)}_{v,t}, m^{(\ell)}_{v,t}). \tag{7}$$

After L rounds of message-passing, a readout feed-forward layer $\rho : \mathbb{R}^{d_h} \to \mathbb{R}^{d_e}$ produces final asset and investor embeddings:

$$e_{v,t} = \rho(h^{(L)}_{v,t}). \tag{8}$$

When referring to node embeddings in subsequent sections, unless otherwise specified we refer to these final representations $e_{v,t}$. Because all parameters are shared across nodes and layers, this architecture is both permutation invariant and inductive, allowing predictions on unseen investors or assets without retraining. In Section 4, we show that the inductive capability of the model indeed allows it to perform well in cold-start exercises, where we ask the model to forecast the trading behavior for unseen sets of assets or investors that are held out of the training sample.

Training Strategy. The model is trained in two sequential phases, following the "pretrain then fine-tune" paradigm (Devlin et al. 2019; He et al. 2022). In the first phase (self-supervised pretraining), we train the GNN backbone using a masked autoencoder (MAE) objective: the model randomly masks a subset of edges in the graph and learns to reconstruct the masked position sizes, forcing the embeddings to encode co-holding patterns, investor similarity, and asset similarity from the abundant cross-sectional structure of the graph without requiring any trade labels. In the second phase (supervised training), we freeze the MAE head and fine-tune the GNN backbone using the supervised trade prediction head, which provides our estimates of the conditional response functions defined in equation (3).

Prediction Heads. The supervised prediction head takes the form of a hurdle model, motivated by the fact that approximately 40% of existing positions see no change in quantity in any given quarter. This mass of exact zeros reflects the fact that many portfolio positions are simply held without adjustment in a given period, whether due to fixed costs of trading, inattention, or the absence of a motive to rebalance. A standard regression task would devote substantial capacity to fitting this point mass at zero, at the expense of accurately predicting the magnitude of trades that do occur. The hurdle model decomposes the prediction into two components: (i) an extensive margin prediction of whether a trade occurs at all, and (ii) an intensive margin prediction of the trade's magnitude, conditional on it occurring. The hurdle prediction head uses the concatenated investor and asset embeddings $(e_{i,t}, e_{a,t})$ together with the aggregate state ζ_{t+1} as inputs, branching into classification logits $\hat{c}_{ia,t+1}$ and a regression prediction $\hat{m}_{ia,t+1}$. The combined prediction is:

$$\hat{y}_{ia,t+1} = \sigma(\hat{c}_{ia,t+1}) \cdot \hat{m}_{ia,t+1}, \tag{9}$$

where $\sigma(\cdot)$ is the sigmoid function. The supervised objective combines binary cross-entropy for the extensive margin and mean squared error for the intensive margin. The MAE and supervised losses, along with the full specification of the training procedure, are detailed in Appendix B. We optimize all model parameters using the AdamW optimizer (Kingma 2014; Loshchilov and Hutter 2018).

The model architecture is summarized visually in Figure 1. A full enumeration of all learnable components and the parameter vector Θ is provided in Appendix B.

Efficiency of Graph-Based Architectures for Holdings Data. Before moving on the empirical implementation, we discuss more precisely the sense in which message-passing, graph-based architectures are parameter-efficient in the context of holdings-based problems. To do this, we lay out a few definitions. Let $W \in \mathbb{R}^{I\times N}$ be the full holdings matrix with entries w_{ia}, and let $f\colon \mathbb{R}^{I\times N} \to \mathbb{R}^d$ be a functional acting on the graph $\mathcal{G}$ represented by W. A continuous graph functional is permutation-invariant if, for all permutation matrices $P_1 \in \mathbb{R}^{I\times I}$, $P_2 \in \mathbb{R}^{N\times N}$, it satisfies $f(P_1 W P_2^T) = f(W)$. Informally, permutation invariance means that if we were to arbitrarily relabel columns and rows of the holdings matrix (i.e., investors and assets), the output of f would remain the same. All regulatory or prediction targets we care about (future trading patterns, systemic risk scores, etc.) are assumed to lie in this family, reflecting the economics of the problem.

A well-known idea in the literature on graph deep learning is that in order to represent a permutation-invariant mapping with the fewest parameters, one should enforce permutation invariance via shared (message-passing) parameters (Zaheer et al. 2017, Maron et al. 2018, Xu et al. 2018). This is the sense in which the models are sample-efficient. For illustration, compare two classes of models. First, consider the class of GNNs which implement permutation-invariant message-passing layers as described above, with shared parameters. Second, consider the class of sequence or grid networks that act on the flattened matrix vec(W) under a fixed but arbitrary ordering of rows and columns (this class includes recurrent neural networks, convolutional neural networks, sequence

Table 1: **Summary statistics**

	Mean	Std	P10	Median	P90	N
Panel A: Graph structure (per quarter)						
Investors	17,751	6,290	9,121	17,408	25,389	72
Assets	33,302	11,623	16,060	35,178	46,609	72
Holdings (edges)	2,310,818	1,172,503	900,260	2,043,472	4,091,039	72
Positions per investor	122.8	22.6	98.7	115.8	160.5	72
Holders per asset	65.6	13.2	55.7	58.5	88.2	72
Graph density (%)	0.406	0.125	0.307	0.352	0.615	72
Panel B: Holdings characteristics (pooled)						
Log holding value	12.60	3.58	9.44	13.11	16.01	166,378,929
Holding value ($M)	5.8	29.9	0.0	0.5	9.0	166,378,929
Trade target ($y_{ia,t}$)	0.005	0.899	-0.277	0.074	0.348	149,755,712
Panel C: Investor characteristics (pooled)						
Total AUM ($M)	790.5	4929.1	13.4	120.3	1259.0	1,270,517
Number of positions	130.26	323.75	5.00	49.00	282.00	1,278,103
Equity share	0.49	0.47	0.00	0.56	1.00	1,278,103
Bond share	0.33	0.45	0.00	0.00	1.00	1,278,103
Panel D: Asset characteristics (pooled)						
Total held value ($M)	418.9	2149.7	7.7	78.2	644.7	2,397,769
Number of holders	69.40	145.68	2.00	23.00	165.00	2,397,769
Coupon (%)	4.60	7.81	1.25	4.75	7.31	1,335,690
Years to maturity	9.10	9.93	1.37	5.83	24.30	778,007

Notes: Panel A reports summary statistics of the holdings data at the quarterly level, across 72 quarters from 2004Q1 to 2021Q4. Panels B–D report summary statistics pooled across all investor-asset-quarter observations. Holdings data are from Factset and Morningstar and cover non-bank financial intermediaries including mutual funds, ETFs, separate accounts, pensions, and insurance companies. Holding value is the dollar value of each position. Trade targets are the log position quantity change, $\log(q_{ia,t+1}/q_{ia,t})$. Investor and asset characteristics are the node features used as model inputs. "Total AUM" is total assets under management; "Total held value" is the aggregate dollar amount held by all investors in a given security.

transformers, and so on). Intuitively, GNNs can approximate permutation-invariant graph functionals without carrying superfluous degrees of freedom that sequence/grid networks would have to "use up" to relearn permutation invariance from data. Message-passing GNNs are efficient because the architecture is itself permutation-invariant, avoiding the need to use additional parameters to learn and enforce it.

4 Empirical Implementation and Results

4.1 Setting, Data, and Model Training

We implement our empirical approach in the setting of non-bank financial intermediation. Since the Great Financial Crisis, tighter bank regulation (e.g., leverage and proprietary-trading constraints) has reduced dealer balance-sheet intermediation and pushed a larger share of risk-taking and liquidity transformation into non-banks, such as money market funds, funds holding bonds and collateralized loan obligations, ETFs, insurers, and pensions. These institutions now intermediate a substantial fraction of tradable credit and duration risk and are subject to fire-sale amplification mechanisms such as runnable or flow-sensitive funding and mark-to-market constraints (Chen et al. 2010; Goldstein et al. 2017; Aramonte et al. 2023; Coppola 2025). Therefore they have become central to episodes where widespread price dislocations occur: for instance, acute liquidity needs by bond mutual funds played a key role in debt market disruptions in the first quarter of 2020 (Haddad, Moreira and Muir 2021; Ma, Xiao and Zeng 2022).

We train our deep learning model on quarterly institutional holdings from Factset and Morningstar, starting in 2004Q1, which cover a broad range of non-bank intermediaries including mutual funds, ETFs, separate accounts, pensions, and insurance companies. The holdings data gives us observations of the positions graph $\mathcal{G}_t$ for each quarter's cross-section, and we also use it to construct the trade outcomes $y_{ia,t+1}$. Table 1 reports summary statistics for the holdings data.

We evaluate the model using two complementary out-of-sample strategies, and we report results under both throughout the paper. The first is a *static split*, in which quarters are randomly partitioned into training and validation sets; this approach maximizes the available training data and provides a pooled measure of predictive accuracy. The second is a *walk-forward* evaluation, in which the model is retrained from scratch each year on an expanding window of past data and tested strictly on the subsequent year's quarters, mimicking real-time regulatory deployment. The walk-forward evaluation spans six annual windows from 2015 to 2020, with the final window providing a particularly salient test during a crisis event: the model is trained only on pre-crisis data and then evaluated on the Covid-19 stress episode (2020q1).

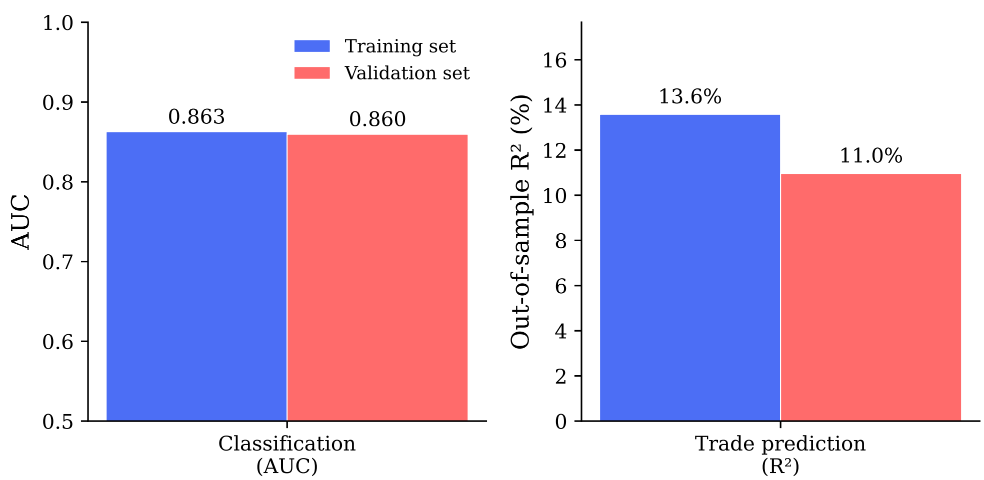
We construct the node feature vectors x_v using reference information from Factset, Morningstar, and the Global Capital Allocation Project (GCAP) security master file (Coppola et al. 2021, Coppola 2025). For assets, the feature vectors x_v include asset class, currency of denomination, amount

Table 2: **Model hyperparameters**

Architecture	
Hidden dimension (d_h)	256
Embedding dimension (d_e)	128
Message-passing layers (L)	3
Attention heads (S_A)	4
Categorical embedding dim (d_c)	16
Dropout rate	0.1
Conditioning	
Basis expansion dim	16
Type embedding dim	8
Response vector dim	16
Training	
MAE pretrain epochs	50
Supervised fine-tune epochs	500 (early stopping)
Learning rate	10^{-3}
Weight decay	10^{-2}
Edge masking rate (MAE)	0.35

Notes: We list the hyperparameters used for our graph transformer architecture, the type-stratified conditioning module, and the two-phase training procedure.

Figure 2: **Performance metrics: static OOS split**



Notes: We plot the out-of-sample performance of the trade prediction hurdle model's two components under the static split: the classification AUC for predicting whether a trade occurs (left panel) and the regression R^2 on nonzero $y_{ia,t+1}$ targets (right panel). The blue bars show performance on the training set, while the red bars show out-of-sample performance on the validation set.

outstanding, number of holders, average position size, standard deviation of position size, as well as bond sub-class and coupon for debt securities. For investors, they include institution type (such as open-end mutual funds, ETFs, separate accounts, etc.), manager style (including flags for active vs. passive portfolio management and strategy types), total AUM, number of positions, average position size, and standard deviation of position size.[5]

Hyperparameters are chosen as in Table 2. We set the hidden dimension to $d_h = 256$ and the final embeddings dimensionality to $d_e = 128$. We use $L = 3$ layers of message-passing with $S_A = 4$ attention heads per layer. We do not increase L beyond this number to prevent the over-smoothing problem, whereby the node embeddings would converge to similar values: intuitively, over-smoothing occurs for higher numbers of message-passing iterations since each consecutive iteration increases the *receptive field* of each node, i.e. the set of nodes that the final-layer embeddings attend to, and for high L values the receptive fields of all nodes converge to the largest possible field, which is the set of all nodes in the graph. The backbone and hurdle head together have approximately 1.3 million parameters.

We introduce dropout during training for additional regularization, with a dropout rate of 0.1. The AdamW optimizer uses a starting learning rate of 10^{-3} with weight decay of 10^{-2} and learning rate reduction on plateau. The self-supervised MAE pretraining phase runs for 50 epochs with a 35% edge masking rate; the supervised fine-tuning phase runs for up to 500 epochs with early stopping (patience of 5 epochs) based on the validation regression correlation. We train the model on NVIDIA H100 GPUs.

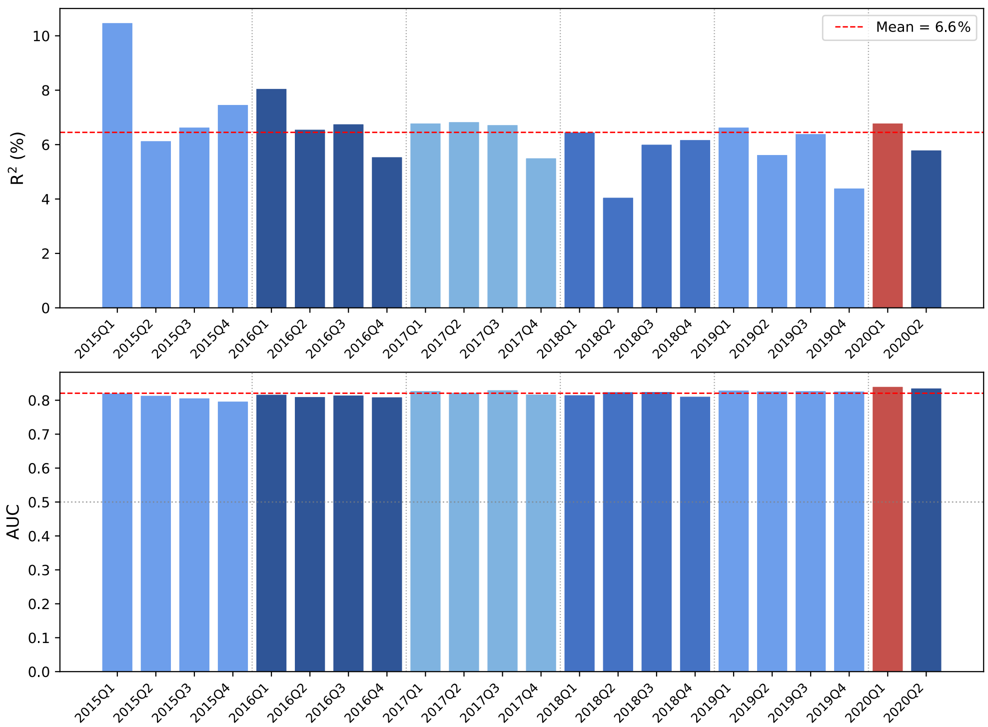
4.2 Assessing the Model's Predictive Performance

We evaluate the model under both out-of-sample strategies. Under the static split, the hurdle model achieves an out-of-sample classification AUC of 0.84 and a regression R^2 of 10.8% on nonzero trades, with minimal degradation from training to validation sets (Figure 2). Under the walk-forward evaluation, the model achieves an average R^2 of 6.6% and AUC of 0.823 across the six annual windows (Figure 3, Table 3), with stable performance throughout the evaluation period. The walk-forward R^2 is lower than the static-split R^2 due to two factors. First, the walk-forward windows train on fewer quarters (as few as 36 in the earliest window), reducing the model's effective training sample. Second, the random static split creates potential information leakage through the persistence of the holdings graph. The walk-forward design eliminates this channel entirely and therefore provides a more conservative measure of the model's predictive accuracy in a real-time regulatory deployment. In the 2020 window, the model achieves a walk-forward R^2 of 7.0%, and the per-quarter R^2 for 2020Q1—the peak of the Covid-19 market stress episode—is 6.8%. The classification AUC is nearly identical across both evaluation settings. The fully inductive design,

[5]In principle, our architecture also allows for the use of global features that vary over time but not across nodes during message-passing: these can be introduced as vectors which enter message-passing in the same way for all nodes in a given time period.

sharing parameters across nodes and layers, ensures stable performance on unseen investors and assets, such that the model performs very similarly out-of-sample as it does on the training data.

Figure 3: **Walk-forward out-of-sample R^2 and AUC, by quarter**



Notes: Per-quarter R^2 (top panel) and classification AUC (bottom panel) from the walk-forward trade prediction evaluation. Each bar represents one quarter that is strictly out of sample: the model used to generate each prediction was trained only on preceding quarters. Different shades of blue indicate different walk-forward windows. The red bar highlights 2020Q1, the onset of the Covid-19 crisis. Red dashed lines show means across periods.

Figure 4 shows a binned scatter plot of predicted vs. realized trades $y_{ia,t+1}$: the OLS slope through the bin means is 0.44, confirming that the model's predictions are informative for all levels of trading outcomes (both buying behavior and selling behavior) and that they are approximately well-calibrated. Figure 5 provides a portfolio sort of realized $y_{ia,t+1}$ by decile of the model's predicted $\hat{y}_{ia,t+1}$: the monotonic increase from the bottom decile to the top decile further confirm that the predictions are informative across the full range of trade outcomes.

Table 4 compares the graph transformer against a suite of benchmark models, all trained on identical trade prediction targets and evaluated out-of-sample on the same held-out quarters. The comparison is organized to isolate the sources of predictive power: from simple forecasting rules and linear methods that use only observable investor and asset characteristics, through flexible nonlinear methods, to deep learning architectures that progressively exploit the relational structure of the holdings data.

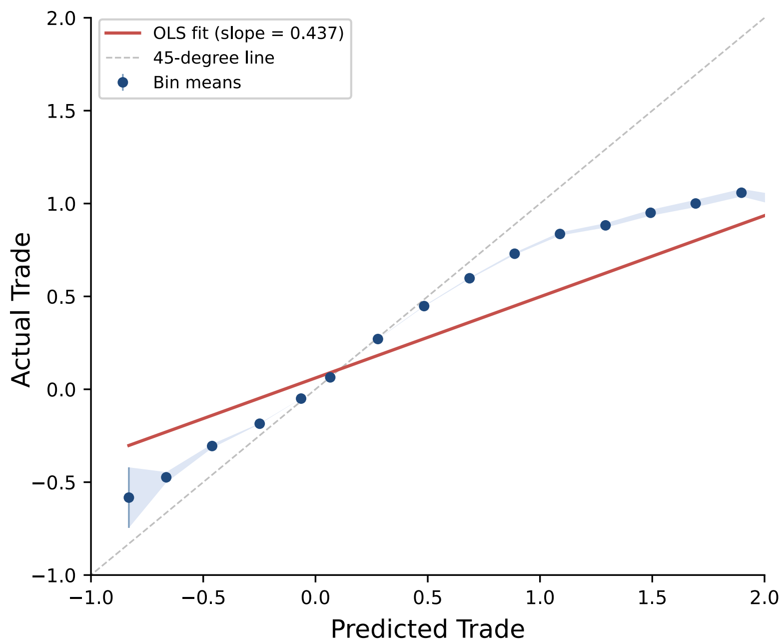
The traditional baselines reveal the difficulty of forecasting trades from characteristics alone.

Table 3: **Walk-forward temporal out-of-sample test, detailed statistics**

Test year	Training Qs	AUC	RegCorr	R^2 (%)	CombCorr	Observations
2015	36	0.809	0.297	8.4	0.256	9,295,984
2016	39	0.813	0.277	6.7	0.223	10,405,466
2017	42	0.825	0.283	6.5	0.207	10,804,831
2018	45	0.819	0.263	5.7	0.214	11,735,336
2019	48	0.828	0.252	5.8	0.210	13,107,196
2020	52	0.839	0.289	7.0	0.232	13,415,123
Average	—	**0.823**	**0.276**	**6.6**	**0.223**	68,763,936

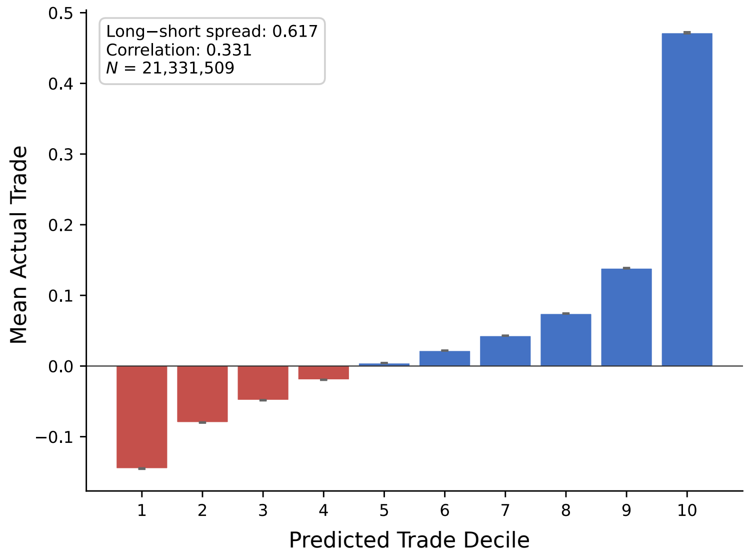
Notes: We show detailed results from the walk-forward out-of-sample test for the trade prediction task. The model is trained from scratch in each window using MAE pretraining followed by supervised training. For each window, we show the number of training quarters. AUC measures classification of trade vs. no-trade. Regression correlation (RegCorr) and R^2 are computed on non-zero target edges. Combined correlation (CombCorr) uses combined predictions ($\sigma(\text{cls}) \times \text{reg}$) from the full hurdle model.

Figure 4: **Binned scatterplot: predicted vs. actual trades** $y_{ia,t+1}$



Notes: Equal-width binned scatter plot of out-of-sample predicted trades $\hat{y}_{ia,t+1}$ (horizontal axis) against realized trades $y_{ia,t+1}$ (vertical axis). Each dot is the mean of one bin; shaded band shows 95% confidence intervals. The red line is the OLS fit through the bin means; the dashed grey line is the 45-degree reference.

Figure 5: **Portfolio sort: realized trades by decile of predicted $\hat{y}_{ia,t+1}$**



Notes: We sort all out-of-sample investor-asset-quarter observations into deciles based on the model's predicted trades $\hat{y}_{ia,t+1}$, and we plot the mean realized trade $y_{ia,t+1}$ within each decile. The sample pools nonzero trade targets across all out-of-sample quarters. Error bars show 95% confidence intervals for the decile means. Realized outcomes are winsorized at the 1st and 99th percentiles to limit the influence of extreme trades from small initial positions. The long-short spread is the difference in mean realized $y_{ia,t+1}$ between the top and bottom deciles.

A persistence forecast—which predicts that each investor will repeat last quarter's trade in each asset—produces a negative R^2: investors who bought last quarter are, if anything, less likely to buy again. Ridge regression on investor and asset characteristics achieves an R^2 of just 2.1%, and gradient-boosted trees (XGBoost), which can capture nonlinear interactions among the same features, reach only 1.7%. The lesson from these baselines is that observable characteristics of investors and assets, even combined with flexible nonlinear methods, explain little of the cross-sectional variation in trading behavior. The predictive signal lies predominantly in the structure of who holds what, and how those positions relate to one another across the network.

The deep learning models, which can learn latent representations of investors and assets from the structure of the data, offer dramatic improvements. A two-tower recommender system—which learns separate latent embeddings for investors and assets and scores their interactions via an inner product, in the spirit of collaborative filtering—achieves an R^2 of 7.8%, roughly a fourfold improvement over the best traditional baseline: we emphasize that the two-tower recommender system is also our original contribution, and not a benchmark from the literature. The graph transformer, which combines attention-weighted message passing with self-supervised pretraining, leads by a significant margin at 10.8%. This progression—from no relational structure, to latent interaction patterns, to explicit graph-based information propagation—isolates the contribution of modeling the holdings network directly. The neural models are inductive, meaning they generalize to previously unseen investors and assets without retraining, a property essential for real-time regulatory deployment where new entities continuously enter the data. The "WF R^2" column confirms that the ranking of models is preserved under the walk-forward evaluation, with the graph transformer again leading (with a more than 50% improvement in walk-forward out-of-sample R-squared compared to the next best model).

Table 4: **Trade prediction: comparison with alternative benchmarks**

Model	Graph	Inductive	AUC	R^2 (%)	WF R^2 (%)	Corr
Panel A: Traditional baselines						
Persistence (lagged $y_{ia,t+1}$)			0.700	<0	<0	-0.054
Ridge regression			0.483	2.1	1.7	0.153
Gradient boosting			0.721	1.7	1.4	0.177
Panel B: Neural baselines						
Two-tower recommender system (our contribution)		✓	0.805	7.8	4.2	0.284
Graph transformer (our contribution)	✓	✓	**0.840**	**10.8**	**6.6**	**0.329**

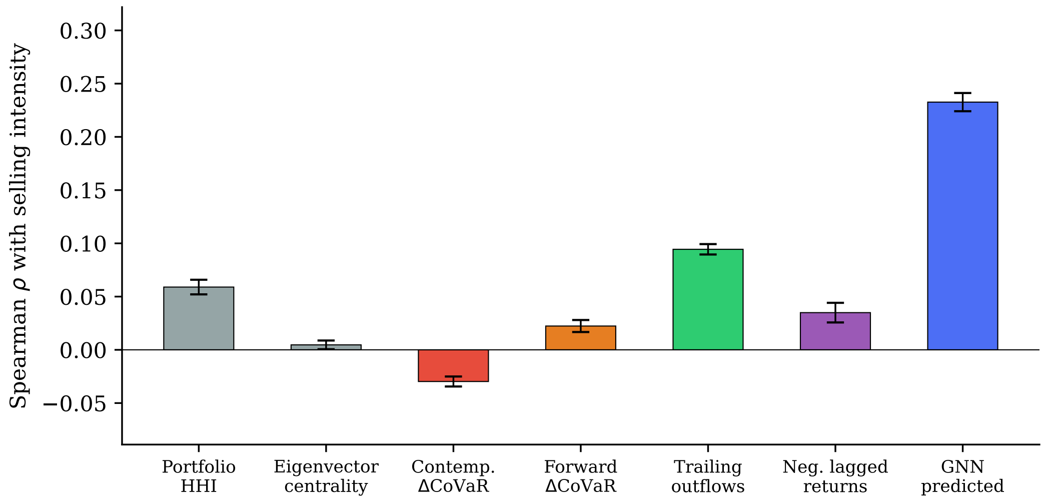
Notes: All models predict trades $y_{ia,t+1}$ on a held-out test set (N = 13,147,068 investor-asset-quarter observations). "AUC" is the area under the ROC curve for predicting whether a trade occurs (nonzero target). "R^2" and "Corr" (Pearson correlation) are reported on the subset of edges with nonzero targets, measuring regression fit conditional on a trade occurring. "WF R^2" is the average R^2 from an expanding-window walk-forward test, where each model is retrained from scratch in each window and evaluated on future data only. "Graph" indicates models that use the portfolio holdings network structure via message passing. "Inductive" indicates models that can generalize to unseen investors or assets without retraining.

4.3 Explaining the Cross-Section of Returns in Stress Episodes

We next study whether the model's learned embeddings capture economically meaningful risk dimensions. We trained the model to understand and predict portfolio positions and trading behavior in both calm times and market stress periods, which are tasks for which training data is relatively abundant. We now investigate whether the trained embeddings can explain the cross-section of liquidation prices in a particular out-of-sample market event where price dislocations were present: since these are rare events, this task has far less data available, and hence our approach is not to fit the model to it at training time, but rather ask whether the structure learned by the model generalizes to it.

Specifically, we focus on the dynamics of bond markets in the first quarter of 2020, during the Covid crisis: as discussed above, this is an episode that featured rapid and widespread disruptions in debt markets, partly driven by acute liquidity needs of investment funds and other financial intermediaries (Haddad et al. 2021; Ma et al. 2022). The fact that this event is also fully outside of our training sample makes it ideal to study our question of interest. We consider the cross-section of bond returns $r_{a,t}$ in 2020Q1, and for each bond we use the trained graph transformer applied to

Figure 6: **Systemic risk identification: comparing methods**



Notes: We plot the average Spearman rank correlation between each systemic importance measure and realized dollar-weighted selling pressure across investors, computed out of sample. Error bars show standard errors across quarters. Contemporaneous ΔCoVaR follows the Adrian and Brunnermeier (2016) methodology, estimated from monthly fund NAV returns. Forward ΔCoVaR is a linear prediction from lagged observable fund characteristics. Trailing outflows uses the negative of the percentage fund flow lagged one year. Neg. lagged returns uses the negative of the previous quarter's compound gross return. GNN predicted selling uses the model's out-of-sample trade predictions.

Table 5: **Explaining bond price dislocations**

	(1)	**(2)**
Cross-Validated R^2		
Total	.08	.42
Incremental from $e_{a,t-1}$	—	.18
Bond Characteristics ($X_{a,t-1}$)	No	Yes
Observations (N)	4,771	4,771

Notes: We report the out-of-fold adjusted R-squared from gradient boosting models applied to the specification in equation (10), which models returns in the cross-section of bonds in 2020Q1 as a function of the GNN's learned prior-quarter embeddings $e_{a,t-1}$ and security characteristics.

holdings data from 2019 to construct the prior quarter embeddings $e_{a,t-1}$.[6] We estimate empirical models of the form

$$r_{a,t} = f(e_{a,t-1},\, X_{a,t-1}) + \varepsilon_{a,t}, \tag{10}$$

where X_a is a bond characteristics vector including bond rating and residual maturity. Given the high-dimensional nature of the embeddings $e_{a,t-1}$, we estimate a non-linear, nonparametric model. Specifically, we train a gradient boosting model using five-fold cross-validation. Table 5 reports the R-squared values from out-of-fold prediction in the cross-section of bonds using the specification in equation (10). We report the out-of-sample R-squared both from a model which includes only the embeddings (column 1) and a model which includes both the embeddings and bond characteristics (column 2). For the latter, we also report the incremental R-squared from the embeddings, which is the difference in the R-squared between the full model (including both $X_{a,t-1}$ and $e_{a,t-1}$) and a model including only characteristics. The incremental R-squared coming from the embeddings in the full model is 18%, and it is in fact higher than the value from the model which includes only the embeddings (as the full model, by virtue of being non-linear, also allows for interactions between the embeddings and the characteristics). Hence the GNN's learned representations explain a large portion of the variation in the cross-section of bond liquidation prices in this market stress episode, even after accounting for bond characteristics, despite these not being a target of the model's training. Altogether, these results demonstrate the efficacy of graph-based predictive models for real-time macroprudential surveillance.

4.4 A Comparison With Systemic Risk Measures

Next, we consider the perspective of a regulator who is interested in monitoring systemic risk using institution-level metrics. We ask how our deep learning based approach compares to existing measures of systemic risk in identifying institutions that contribute most to selling pressure during stress periods in the non-bank setting that we consider. To evaluate different systemic risk measures, for each investor i and quarter t, we define the realized investor selling intensity as

$$S_{i,t} \;=\; \frac{1}{\mathrm{AUM}_{i,t-1}} \sum_a w_{ia,t-1} \max\!\left(-\frac{q_{ia,t} - q_{ia,t-1}}{q_{ia,t-1}},\, 0\right), \tag{11}$$

which measures the fraction of assets under management that an investor sells in a given quarter. Scaling by $1/\mathrm{AUM}_{i,t-1}$ removes the mechanical size channel (larger investors sell more in absolute terms) and isolates the genuinely informative variation in selling behavior. For each out-of-sample quarter, we compute the Spearman rank correlation between each candidate systemic risk measure and the realized selling intensity across all investors.

[6] We use the sample of bonds that are reportable to TRACE, the transactions database maintained by FINRA. We apply to TRACE the data cleaning steps in Dick-Nielsen (2014), which are common in the literature. TRACE lets us observe the prices at which bonds transact. Quarterly bond returns account for price changes, coupons, and accrued interest, and they are constructed as in Coppola (2025).

We compare seven measures of systemic risk in our non-bank setting. The first is the ΔCoVaR measure introduced by Adrian and Brunnermeier (2016) in a banking context, which quantifies the increase in the financial system's tail risk conditional on a given institution being in distress. We estimate ΔCoVaR using monthly fund NAV returns, with a median of 119 months of data per fund over the 2003–2018 period, defining the system return as the AUM-weighted average monthly return across all funds, analogous to the value-weighted financial sector index used by Adrian and Brunnermeier (2016). For each fund, we estimate the 5th-percentile quantile regression of the system return on the individual fund return.[7] The second metric is a forward measure of ΔCoVaR, obtained by regressing the contemporaneous ΔCoVaR_i on lagged fund characteristics using OLS estimated on training data only, and applying the fitted model out of sample.

The third measure is portfolio concentration, as measured by the HHI of holdings. The fourth is eigenvector centrality of the portfolio overlap network. The fifth is trailing fund outflows, motivated by the flow-driven fire sale channel of Coval and Stafford (2007): funds experiencing outflows must liquidate holdings, so we use the lagged percentage fund outflow as a predictor of selling intensity. The sixth is negative lagged fund returns, motivated by the flow-performance relationship that is well-documented in the fund market (Chevalier and Ellison 1997): poor past returns trigger outflows, which in turn force selling. The seventh is the predicted selling intensity from our GNN model, $\hat{S}_i$, where $\hat{S}_{i,t} = \text{AUM}_{i,t-1}^{-1} \sum_a w_{ia,t-1} \max(-\hat{y}_{ia,t}, 0)$ uses the model's out-of-sample trade predictions.

Figure 6 reports the results for the Spearman rank correlation (across investors) between each systemic risk measure and realized selling intensity. Table 6 also shows the same metrics separately for stress quarters (defined as quarters in which the financial stress index exceeds a threshold, FSI $>$ 1.5) and non-stress quarters. The GNN achieves the highest rank correlation with selling intensity by a wide margin ($\rho = 0.23$). The next strongest measure is trailing fund outflows ($\rho = 0.09$), consistent with the flow-driven fire sale channel, although the GNN outperforms it by a factor of more than two. All other measures achieve significantly smaller correlations: negative lagged returns ($\rho = 0.04$), forward ΔCoVaR from fund characteristics ($\rho = 0.02$), portfolio HHI ($\rho = 0.06$), eigenvector centrality ($\rho = 0.01$), and contemporaneous ΔCoVaR ($\rho = -0.03$). The results are stable across stress and calm quarters.

The economic rationale for this result is instructive, and it highlights a fundamental distinction between the information sets relevant for measuring systemic risk in the banking versus non-bank sectors. In the banking setting for which many systemic risk measures (such as ΔCoVaR) are designed, bank equity returns embed information about leverage, maturity mismatch, and balance sheet interconnections, which are the economic channels through which banks propagate shocks

[7] Let $R_{i,t}$ denote fund i's monthly gross return and $R_{\text{sys},t} = \sum_j w_j R_{j,t} / \sum_j w_j$ the AUM-weighted system return, where w_j is fund j's average assets under management. We estimate $Q_{0.05}(R_{\text{sys},t} \mid R_{i,t}) = \alpha_i + \beta_i R_{i,t}$ and compute $\Delta\text{CoVaR}_i = \hat{\beta}_i(\text{VaR}_{0.05}(R_i) - \text{median}(R_i))$, where $\text{VaR}_{0.05}(R_i)$ is the 5th percentile of fund i's monthly return distribution. Funds with fewer than 36 monthly observations are excluded. The resulting ΔCoVaR measures capture fund-level tail risk contributions estimated from approximately 20,800 funds with sufficient data.

Table 6: **Systemic risk identification: comparing methods**

	Spearman ρ with selling intensity		
Method	All quarters	Stress	Calm
Portfolio HHI	0.059	0.045	0.060
	(0.007)	(0.007)	(0.007)
Eigenvector centrality	0.005	0.003	0.005
	(0.004)	(0.003)	(0.005)
Contemporaneous ΔCoVaR	-0.030	-0.018	-0.031
	(0.005)	(0.010)	(0.005)
Forward ΔCoVaR	0.022	0.038	0.021
	(0.006)	(0.001)	(0.006)
Trailing fund outflows	0.094	0.083	0.096
	(0.005)	(0.011)	(0.005)
Neg. lagged fund returns	0.035	0.006	0.038
	(0.009)	(0.000)	(0.010)
GNN predicted selling intensity	**0.233**	**0.184**	**0.237**
	(0.009)	(0.012)	(0.009)

Notes: Each cell reports the average Spearman rank correlation between the given measure and realized selling intensity $S_{i,t}$, with standard errors across quarters in parentheses. GNN predictions are out of sample. Stress quarters: STLFSI4 $>$ 1.5.

(Adrian and Brunnermeier 2016; Benoit et al. 2017). Larger, more leveraged banks have more volatile returns and stronger co-movement with the financial system, generating for example cross-sectional variation in ΔCoVaR that correlates with systemic importance. For non-bank intermediaries such as mutual funds, however, these leverage-driven channels are largely absent. Fund NAV returns are mechanically determined by portfolio composition, not by balance sheet structure: for example, a \$100 billion equity index fund and a \$100 million equity index fund holding the same stocks have essentially the same return beta with the financial system. The same logic applies to other return-based systemic risk measures such as MES (Acharya, Pedersen, Philippon and Richardson 2017) and SRISK (Brownlees and Engle 2017): since fund NAV returns do not encode the cross-sectional variation in size and holdings structure that drives non-bank selling pressure, measures relying solely on return time-series data face a similar limitation in this sector.

4.5 Heterogeneity and Inductive Generalization Performance

Next, we investigate heterogeneity in the predictive performance of the GNN, and we also conduct "cold start" tests where we explicitly assess the inductive generalization abilities of the model. A natural question is whether the predictive ability of the model comes primarily from relatively more mechanical aspects of the data, such as by correctly assessing the trades of passive index-tracking investors. Table 7 addresses this directly: the "active funds only" row evaluates the model only on

Table 7: **Trade prediction: heterogeneity by investor type and asset class**

	N	AUC	Reg Corr	Reg R^2 (%)	WF R^2 (%)	Share (%)
Panel A: By investor type						
Open-end mutual funds	26.2M	0.837	0.326	10.6	6.8	72.9
ETFs	4.8M	0.902	0.359	12.6	7.1	13.3
Non-fund institutions	4.1M	0.847	0.308	9.5	2.4	11.3
Other funds	899K	0.840	0.302	8.9	5.9	2.5
Active funds only	31.2M	0.839	0.323	10.4	6.1	86.7
Panel B: By asset class						
Common equity	24.5M	0.812	0.334	11.1	6.6	68.2
Corporate bonds	7.0M	0.831	0.311	9.6	6.2	19.5
Sovereign bonds	1.9M	0.814	0.327	10.6	7.6	5.4
Fund shares	1.4M	0.823	0.359	12.9	8.6	3.8
Other fixed income	678K	0.765	0.302	9.0	6.7	1.9
All	**35.9M**	**0.853**	**0.331**	**10.9**	**6.7**	100.0

Notes: Out-of-sample trade prediction performance decomposed by investor type (panel A) and asset class (panel B) using the graph transformer model. AUC measures classification of trading vs non-trading edges. Regression correlation and regression R^2 are computed on the nonzero-target subset. Performance is evaluated on held-out validation and test quarters. WF R^2 reports the pooled walk-forward out-of-sample R^2 from expanding-window retraining.

trades by funds that are classified as active (i.e., that do not passively track an index), and it shows an AUC of 0.839 and regression R^2 of 10.4%. This is quantitatively very similar to the full-sample results. The model's predictive ability is thus not driven by mechanical passive rebalancing. Table 7 also further decomposes the model's out-of-sample trade prediction performance by investor type and asset class, reporting both the classification AUC and the regression R^2 on nonzero $y_{ia,t+1}$ targets. Panel A shows results separately for different types of institutions: open-end mutual funds, ETFs, other funds, and non-fund institutions. Panel B shows the results by asset class. The model performs well across investor types and asset classes, including those (like open-end funds and corporate bonds) that have been at the center of fire sale dynamics in recent episodes of market stress (Haddad, Moreira and Muir 2021; Coppola 2025).

We conduct additional tests to validate the model's inductive generalization, i.e. its ability to make predictions for entities never seen during training. For each experiment, we remove an entire category of investors or assets from all training graphs and retrain the graph transformer model from scratch, then evaluate the trained model on the complete (unmodified) graphs. Table 8 reports the results, including both regression R^2 on nonzero $y_{ia,t+1}$ targets and classification AUC for the binary trade prediction. In all experiments, the model's accuracy on seen edges is not strongly affected by the holdout, indicating that removing entity types does not meaningfully degrade performance on the remaining entities. For the random holdout tests, the gap between held-out and seen R^2 is small (e.g., 9.5% vs. 9.7% for the cold start test where we randomly exclude 20% of assets during training, and 7.6% vs. 9.2% for the test which excludes a random 20% of investors), confirming that the model generalizes to arbitrary unseen entities with little degradation. Even in the most challenging cold start test where we drop an entire asset class (corporate bonds), the GNN continues to do well on the held-out set: in this test, despite not having been trained on any corporate bond observations, the model still generalizes successfully to the unseen asset class and achieves an R^2 of 4.5%.

Table 8: **Cold-start inductive generalization test**

Held-out group	% edges	Reg. Corr.		R^2 (%)		AUC	
	held out	Held-out	Seen	Held-out	Seen	Held-out	Seen
Corporate bonds	19.5	0.231	0.329	4.2	10.7	0.761	0.819
Random 20% investors	21.1	0.307	0.321	7.6	9.2	0.824	0.847
Random 20% assets	20.1	0.312	0.317	9.5	9.7	0.846	0.847

Notes: We show inductive generalization ("cold start") test using the graph transformer model. For each row, the model is trained from scratch with the indicated entity group entirely removed from all training graphs, then evaluated on the complete (unmodified) graphs. "Held-out" edges are those touching at least one held-out entity; "Seen" edges connect only entities present during training. Reg. Corr. and R^2 are computed on nonzero (traded) edges only. AUC measures trade/no-trade classification accuracy. The random investor test holds out 20% of individual investors (consistent across quarters); the random asset test holds out 20% of individual securities.

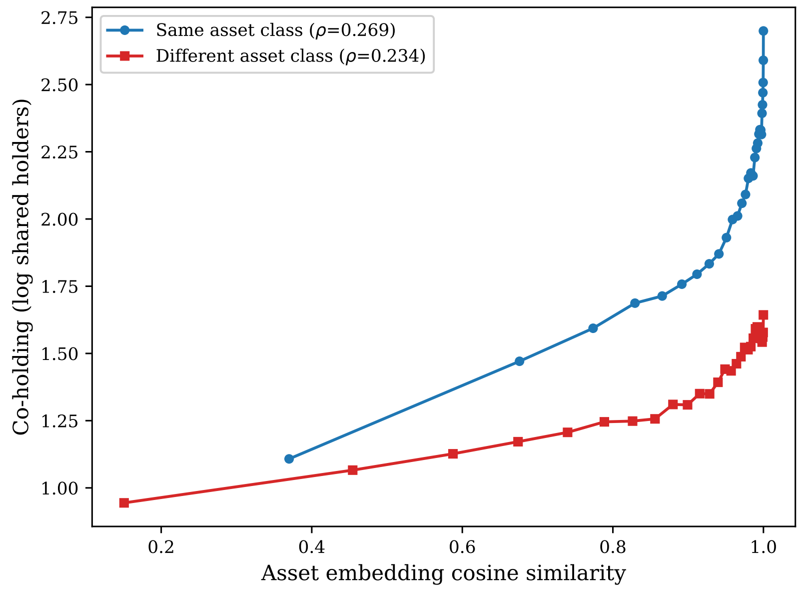
4.6 Economic Content of the Learned Embeddings

To understand what the GNN's learned representations encode, we conduct three complementary analyses using the investor and asset embeddings extracted from the 2020Q1 cross-section. First, we visualize the asset embedding space through a two-dimensional projection using the t-SNE algorithm (shown in Figure A.II). The embeddings exhibit some spatial segregation by asset class, with equities, corporate bonds, government bonds, sovereign bonds, and fund shares occupying distinct regions of the embedding space. Overlap between classes is also present, reflecting assets with mixed investor bases: the spatial organization shows that the GNN's message-passing layers learn to encode fundamental economic distinctions between asset types through the structure of the holdings network.

Second, we assess how much of the embedding variation is explained by observable characteristics. When we jointly regress each embedding dimension on all observable characteristics—including numeric features and one-hot encoded categorical features—the variance-weighted R^2 is 0.54 for investor embeddings and 0.50 for asset embeddings (see Table A.III), indicating that a substantial component of the embedding variation encodes novel structure learned from the holdings network that is not captured by observable characteristics alone.

Third, we test whether the asset embeddings capture *co-holding structure*, i.e. the patterns of common ownership that drive fire-sale contagion. For a sample of 3,000 assets, we compute pairwise

Figure 7: **Asset embedding similarity predicts co-holding**



Notes: Binned scatter plot (30 equal-frequency bins) of pairwise co-holding (log number of shared investors) against pairwise asset embedding cosine similarity, for a sample of 3,000 assets restricted to pairs with at least one shared holder. Blue circles show same-class asset pairs; red squares show different-class pairs.

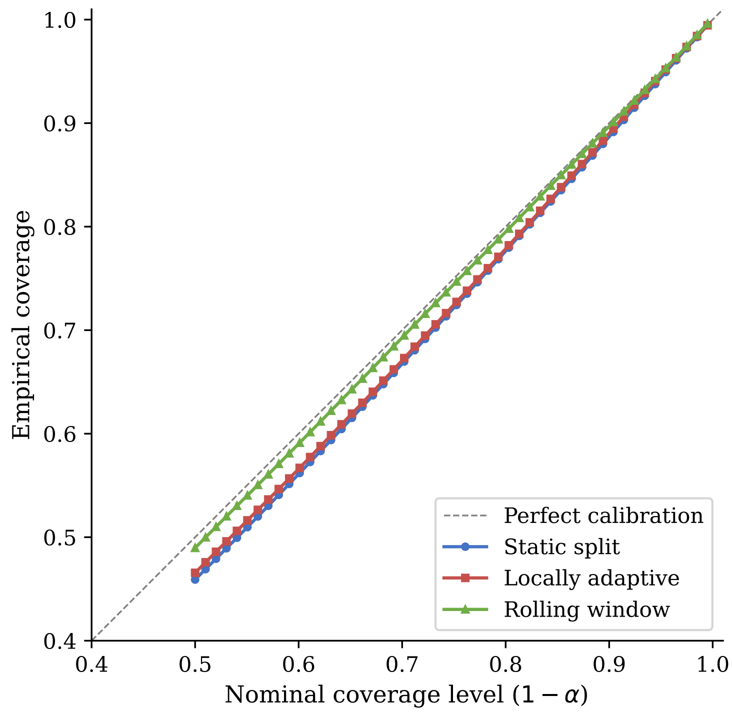
co-holding (the log number of investors that hold both assets) and pairwise embedding cosine similarity, focusing on asset pairs that share at least one holder. Figure 7 displays a binned scatter plot of co-holding against embedding similarity, separately for same-class and different-class asset pairs. The correlation is positive and highly significant in both cases ($r = 0.27$ overall, $p < 0.001$), confirming that the learned asset embeddings encode which securities are held together by the same investors. Crucially, the positive correlation within same-class pairs demonstrates that embedding similarity captures co-holding structure beyond what asset-class labels provide. This is precisely the information the model needs for predicting correlated trades: assets held by the same investors are likely to be traded together during portfolio rebalancing, and the GNN's embeddings internalize this common-ownership signal through message passing over the bipartite holdings network.

4.7 Conformal Prediction Intervals

Point predictions are especially useful for regulatory decision-making if they are supplemented with measures of uncertainty: a supervisor who observes a predicted trade outcome $\widehat{y}_{ia,t+1} = 0.5$ needs to know whether the plausible range is $[0.3, 0.7]$ or $[-1.5, 2.5]$ before acting. To provide useful ranges, we accompany each point forecast with a prediction interval using split conformal prediction (Vovk et al., 2005; Lei et al., 2018).

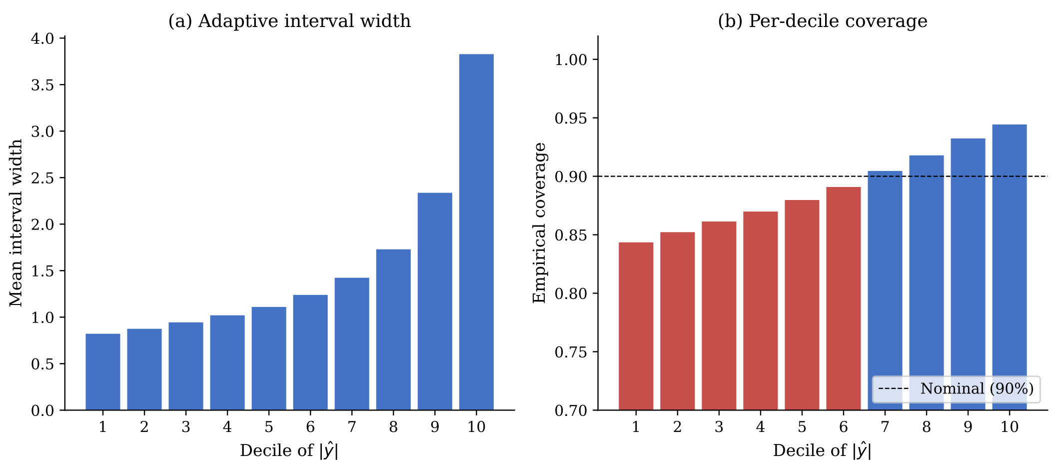
In its standard form, for a target coverage level $1 - \alpha$, split conformal prediction guarantees finite-sample marginal coverage $\Pr(y_{ia,t+1} \in C_{1-\alpha}(e_{i,t}, e_{a,t}, \zeta_{t+1})) \geq 1 - \alpha$ under the assumption of

Figure 8: **Conformal prediction: coverage calibration**



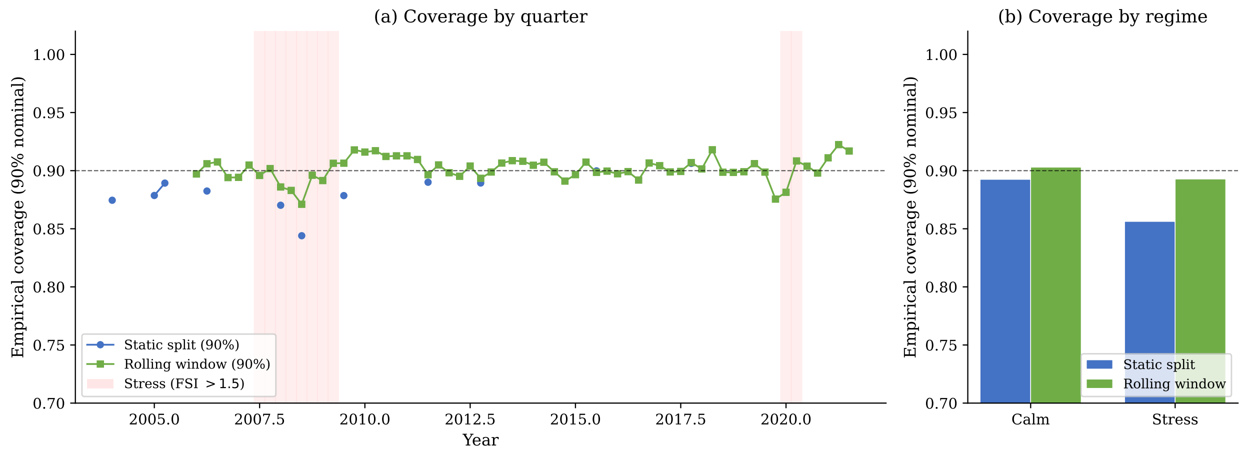
Notes: Empirical coverage against nominal coverage for three conformal methods: static split (calibrate once on 11 fixed validation quarters), locally adaptive (heteroscedastic intervals via residual normalization), and rolling window (recalibrate on the preceding 8 quarters before each evaluation quarter). The dashed line indicates perfect calibration.

Figure 9: **Adaptive interval width and per-decile coverage**



Notes: Locally-adaptive conformal intervals at 90% nominal coverage. Panel A shows mean interval width by decile of $|\widehat{y}|$. Panel B shows per-decile empirical coverage; bars below the dashed 90% line are highlighted.

Figure 10: **Coverage robustness: time series and stress regimes**



Notes: Panel A: per-quarter empirical coverage at 90% nominal for static split and rolling-window conformal. Shaded regions indicate stress quarters (FSI > 1.5). Panel B: coverage by financial regime (calm vs. stress) for both methods. The rolling window achieves near-nominal coverage in both regimes.

exchangeability of calibration and test observations (Angelopoulos and Bates, 2023). Before moving on to the implementation of the conformal prediction methodology, we note that this formal coverage guarantee may not apply directly to our setting given plausible departures from the exchangeability assumption, since the data are a large panel subject to both cross-sectional dependencies and to an environment that can shift over time. Because of this, we use the conformal prediction methodology simply as a distribution-free calibration device, and we evaluate coverage validity purely empirically across time and regimes. In ongoing work, we are exploring the application of covariate-shift conformal methods (Tibshirani et al., 2019) and conformal procedures designed for dependent data (Barber et al., 2023; Chernozhukov et al., 2018) to this setting.

We partition the data into (i) a training set used to fit the predictive model, (ii) a calibration set used only to compute nonconformity scores, and (iii) a held-out test set for evaluation. For each calibration pair $(i, a) \in \mathcal{I}_{\text{cal}}$, we compute the absolute residual $s_{ia} = |y_{ia,t+1} - \widehat{y}_{ia,t+1}|$. The split conformal interval at coverage level $1 - \alpha$ is

$$C_{1-\alpha} = [\widehat{y}_{ia,t+1} \pm \widehat{q}_{1-\alpha}], \tag{12}$$

where $\widehat{q}_{1-\alpha}$ is the $\lceil (n+1)(1-\alpha) \rceil / n$ quantile of the calibration scores and $n = |\mathcal{I}_{\text{cal}}|$. We report three variants. First, we report results from a static split, calibrating once on 11 validation quarters and evaluating on 11 test quarters. Second, we adopt a locally adaptive variant that normalizes residuals by the local median absolute deviation within deciles of $|\widehat{y}_{ia,t+1}|$ to produce heteroscedastic intervals (Lei et al., 2018). Third, we adopt a rolling window variant that recalibrates on the preceding 8 quarters before each evaluation quarter, trading the fixed-calibration guarantee for adaptivity to distributional drift.

Figure 8 reports empirical coverage for the estimated prediction intervals against nominal coverage. At the 95% level, all three methods track the nominal level closely. The key difference emerges at 90%: the static split exhibits mild under-coverage, consistent with distributional shift, while rolling-window recalibration tracks the nominal level more accurately. Figure 10 examines coverage stability across time and regimes at 90% nominal. The rolling window achieves coverage ranging from 88.6% to 91.6% across all evaluated quarters. The static split shows a calm-stress gap (88.9% vs. 86.9%), which the rolling window largely closes (90.3% vs. 89.9%). This near-uniformity across regimes is encouraging for regulatory credibility.[8]

5 A Theory of Optimal Policy with Predictive Models

The empirical results in the preceding sections demonstrate that graph-based predictive models can accurately forecast institutional trading and recover economically meaningful measures of systemic risk. These objects are of independent interest for financial stability monitoring. We now develop a tractable equilibrium model of fire sales and optimal macroprudential intervention that provides one framework for interpreting the policy and welfare value of the empirical forecasts from the preceding sections. We show that even in an environment subject to the usual Lucas critique, high-dimensional predictive models have value to the regulator by allowing for better cross-sectional policy targeting.

Model Overview. In our theory, we model a three-period economy with intermediaries and a government regulator. The model builds upon canonical fire sales environments. In the first period, financial intermediaries choose portfolios. In the second, intermediaries face constraints (e.g., pledgeability and collateral constraints) that force them to sell some assets prior to maturity. The key fire sale externalities arise because these assets are sold to second-best users whose productivity depends on the amount purchased. Finally, any assets held to maturity pay off in the third period.

The regulator can intervene in the second period to try to manage fire sales. We allow the regulator to employ a (potentially incomplete) set of liquidation wedges that affect intermediaries' choice of which assets to liquidate. Formally, liquidation wedges take the form of revenue-neutral taxes on selling an asset, although we later show that results extend to applying subsidies for retaining an asset. The key informational friction is that the regulator faces uncertainty over the mapping from intermediaries' asset positions and the policy intervention to realized liquidations and fire sale prices. The regulator has a prior over this mapping. Before undertaking the intervention, the regulator can choose to deploy a model that delivers a signal about the latent fundamentals (e.g., predicted sales volumes or liquidation discounts). The regulator can then design its intervention

[8]Importantly, we note that these are marginal coverage rates pooled across all investor-asset pairs (i, a) within each quarter. Conditional coverage for specific investor types, asset classes, or individual entities may of course differ. Figure 9 provides partial evidence: locally-adaptive intervals at 90% nominal show coverage by decile of $|\widehat{y}_{ia,t+1}|$ that is approximately uniform, though the lowest deciles fall to roughly 83%, indicating that positions with the smallest predicted trades have somewhat less reliable intervals.

based on the model used and the signal produced. Crucially, models can differ in what aspects of the system they inform. A model may provide strong predictive content (about liquidations and prices) but little information about the causal effects of interventions, and vice versa.

We characterize the regulator's optimal ex post policy rule as a function of its Bayesian posterior over key primitives. The regulator's optimal rule depends on the product between the predicted causal impact of the policy (a structural elasticity to the policy instruments) and the predicted social benefit of the policy. The social benefit of the policy, deriving from raising the fire sale price, is determined by the amount of each type of asset being sold in the no-intervention equilibrium: this is the key sufficient statistic that governs the optimal targeting of the policy intervention in the cross-section. As a consequence, even a purely predictive model can improve welfare if its forecasts accurately recover these sufficient statistics for investors and assets where the regulator has prior knowledge about the causal impact of the policy intervention. For example, if the regulator knows that its intervention will have a strong causal effect on fire sale prices in certain markets, then predictive models that are informative precisely about forced sales in those markets have particular potential to generate welfare gains. This yields a complementarity between causal knowledge of policy interventions and predictive models that inform the social benefit of intervention.

Setup. There are N assets. There are I intermediary types (each of equal measure), with a representative intermediary of each type i. There is also a representative arbitrageur. The model has a Beginning-Middle-End structure. In the Beginning, initial asset positions are undertaken. In the Middle, intermediaries may be forced to sell assets prior to maturity to arbitrageurs, who are second best users. In the End, payoffs are distributed and consumption occurs.

Intermediaries. Intermediaries are risk neutral. In the Beginning, intermediary i invests in a vector $q_i = (q_{i1}, \dots, q_{iN})^T$ of assets. If $q_{in} < 0$, then intermediary i has undertaken a negative investment (shorting) asset n.[9] The cost to intermediary i of producing the asset vector q_i is $C_i(q_i) = p_i^T q_i - \frac{1}{2} q_i^T H_i^q q_i$, where p_{in} is the per-unit cost to i of producing asset n and where $p_i = (p_{i1}, \dots, p_{iN})^T$. The cost component $q_i^T H_i^q q_i$ is a quadratic adjustment/holding cost, where H_i^q is an $N \times N$ matrix. If held to maturity, intermediary i's holdings of asset n will produce a per-unit return R_{in} in the End, with $R_i = (R_{i1}, \dots, R_{iN})^T$.

In the Middle, intermediary i can sell assets prior to maturity. We denote $\ell_{in} \geq 0$ to be sales by intermediary i at endogenous price γ_n, with $\ell_i = (\ell_{i1}, \dots, \ell_{iN})^T$ and $\gamma = (\gamma_1, \dots, \gamma_N)^T$. Intermediary i faces an adjustment cost $\frac{1}{2} \ell_i^T H_i^\ell \ell_i$ on asset sales, where H_i^ℓ is $N \times N$. Assets will be sold at a discount on their fundamental value ($\gamma < R_i$, see below), and intermediary i faces a set of "rollover constraints" that force asset sales. This set of M constraints is given by

$$A_i^q q_i + \rho_i \leq A_i^\ell \ell_i, \tag{13}$$

[9] We could endow intermediaries with a stock of assets, but for expositional convenience we set that stock to 0.

where A_i^q, A_i^ℓ are $M \times N$ and ρ_i is $M \times 1$. For example, equation 13 can capture constraints on asset positions (e.g., a limit on debt) or a requirement to raise funds based on asset holdings (e.g., a cost of maintaining the project).[10]

In the End, intermediary i realizes payoff on assets held to maturity and consumes. Intermediary i's total payoff (consumption) in the End, inclusive of adjustment costs, is

$$U_i = q_i^T(R_i - p_i) - \ell_i^T(R_i - \gamma) - \frac{1}{2}q_i^T H_i^q q_i - \frac{1}{2}\ell_i^T H_i^\ell \ell_i. \tag{14}$$

Arbitrageurs. A representative arbitrageur is a second-best user of intermediary assets. If the arbitrageur purchases a vector $L = (L_1, \ldots, L_N)^T$ of intermediary assets in the Middle, the arbitrageur can use them in a production technology to produce $\mathcal{F}(L) = L^T\overline{\gamma} - \frac{1}{2}L^T\Gamma L$ units of the consumption good in the End, where $\overline{\gamma}$ is $N \times 1$ and Γ is $N \times N$. The representative arbitrageur's payoff is

$$U_A = L^T(\overline{\gamma} - \gamma) - \frac{1}{2}L^T\Gamma L. \tag{15}$$

Information Structure and Timing. Although all model parameters are determined in the Beginning, all agents in the Beginning are uncertain about the true values of the parameters $\Phi = \{A_i^q, A_i^\ell, H_i^\ell, \rho_i, R_i, \overline{\gamma}\}$. That is, agents are uncertain as to the true parameters underlying the rollover constraint (equation 13), the asset return R_i, the arbitrageurs' baseline productivity $\overline{\gamma}$, and the liquidation adjustment cost H_i^ℓ. All agents have a common prior $\Phi \sim \mu_0$ in the Beginning. In the Middle before asset sales and purchases are chosen, the true model parameters become common knowledge of private agents. After becoming common knowledge, intermediaries choose asset liquidations and arbitrageurs choose asset purchases.[11]

Market Clearing. Markets must clear for liquidations in the Middle, that is

$$L = \sum_i \ell_i. \tag{16}$$

[10] We simplify analysis by not having equation 13 depend on the liquidation price γ, as for example in price-dependent collateral constraints. This enables us to maintain a linear-quadratic structure throughout the paper. It is straightforward to extend analysis to include prices in constraints, but the characterization of the ex-ante optimal portfolio would no longer admit a closed-form solution.

[11] Assuming that private agents and the regulator (see below) have a common prior in the Beginning simplifies analysis because it prevents the regulator from learning information about these parameters from inference about private sector beliefs based on the asset allocation. It also eliminates a regulatory incentive based on different beliefs the regulator and agents (e.g., Fontanier 2025.)

Assuming Γ is known to all agents ex ante simplifies analysis by eliminating the ability of a regulator to learn about the price impact of liquidations from observing a signal of γ or ℓ. This will allow us to fully separate predictive and causal channels in our framework. Absent this assumption, predictive models that inform a regulator about γ and ℓ might have even more value ex post because they would also allow the regulator to learn about these structural parameters that determine the causal impact of a policy intervention (even if very little information is learned).

Competitive Equilibrium. We define a competitive equilibrium as follows.

Definition 1. *A competitive equilibrium of the model, given true model parameters Φ, is a vector of prices γ and a set of allocations $\{q_i, \ell_i, L\}$ such that:*

1. *In the Middle, taking as given asset allocations $\{q_i\}$ and model parameters Φ:*
   (a) *Intermediary i chooses ℓ_i to maximize utility (equation 14) subject to the rollover constraint (13), taking prices γ as given.*
   (b) *Arbitrageurs choose L maximize utility (equation 15), taking prices γ as given.*
   (c) *The liquidation markets clear (equation 16).*
2. *In the Beginning:*
   (a) *Intermediary i chooses q_i to maximize expected utility $\mathbb{E}_0[U_i]$, where $\mathbb{E}_0$ denotes the expectation given the prior μ_0 over model parameters Φ.*

5.1 Regulator's Model Design and Intervention in the Middle

In the Middle, a regulator is able to intervene in order to try to manage the fire sale price impact of liquidations. Formally, the regulator can impose a vector $\tau_i = (\tau_{i1}, \dots, \tau_{iN})^T$ of revenue-neutral liquidation wedges on each intermediary i, which alter the intermediary's perceived price for selling the asset.[12] τ_{in} represents a tax on selling asset n, with $\tau_{in} < 0$ being a subsidy for sale. As a result, intermediary i's payoff in the End is modified to be

$$U_i - (\ell_i^T - \ell_i^{*T})\tau_i \tag{17}$$

where $\ell_i^{*T}\tau_i$ is equilibrium revenue remissions based on the equilibrium asset liquidations ℓ_i^* of intermediary i. Intermediaries take revenue remissions as given. We allow for the possibility that the regulator has potentially incomplete instruments, represented by a regulatory cost $\delta(\tau) = \frac{1}{2}\tau^T\Delta\tau$, where Δ is $NI \times NI$.[13]

Unlike private agents, the regulator does not learn the true model parameters Φ. Instead, the regulator has to use a *model* to make an inference about the true parameters. The regulator's *model* $M \in \mathcal{M}$ formally is a process of drawing a signal s of the parameters. The signal updates the regulator's posterior distribution to $\Phi \sim \mu_p|s, M$. The regulator must choose the wedges τ before private agents move, and so the regulator cannot obtain any new information from observing the market before setting regulation (apart from the signal drawn).

[12] In Section 5.8, we instead assume the regulator must use asset holding subsidies rather than liquidation taxes. The results in the Middle are identical, but the asset holding subsidies introduce additional moral hazard in the Beginning.

[13] One could instead model incompleteness as a restriction $\Delta(\tau) \leq 0$ in which case the regulator's Lagrangian will be $\mathbb{E}[\sum_i U_i|\Gamma, M] - \lambda\Delta(\tau)$ where λ is the Lagrange multiplier. This is akin to the reduced-form cost $\delta(\tau) = \lambda\Delta(\tau)$ except that λ is endogenous.

To simplify exposition, we introduce an assumption of matrix symmetry that we maintain throughout the paper.

Assumption 1. *The matrices $H_i^q, H_i^\ell, \Gamma, \Delta$ are symmetric.*

Impact of Regulatory Intervention. To solve the regulator's optimum, we begin by characterizing the impact of the regulator's wedges $\tau = (\tau_1^T, \ldots, \tau_I^T)^T$ on the equilibrium in the Middle. Our model is substantially simplified by the information structure: because private agents directly observe Φ in the Middle, for a given vector of asset allocations $q = (q_1^T, \ldots, q_I^T)^T$ the equilibrium in the Middle does not depend on the regulator's choice of model M or the realized signal s except through the choice of wedges τ.

The linear-quadratic structure of preferences and the rollover constraint leads to a characterization of the equilibrium as a simple linear system of equations. The following Lemma characterizes this equilibrium.

Lemma 1. *Given asset allocations q, true parameters Φ, and regulatory wedges τ, the equilibrium in the Middle is given by*

$$\ell_i = \overline{\ell}_i + \Lambda_i^q q_i - \Lambda_i^\tau \tau_i - \sum_{j=1}^{N} \left[\Lambda_j^{q,e} q_j^* - \Lambda_j^{\tau,e} \tau_j^* \right] \tag{18}$$

$$\gamma = \overline{\gamma} - \Gamma \sum_i \ell_i \tag{19}$$

where $\overline{\ell}_i$ $(N \times 1)$ and $\Lambda_i^q, \Lambda_i^\tau, \Lambda_i^{q,e}, \Lambda_i^{\tau,e}$ $(N \times N)$ are defined in the proof.

The characterization of the equilibrium in Lemma 1 is intuitive. Liquidations start from a benchmark $\overline{\ell}_i$ and increase (for positive Λ_i^q) in asset holdings while decreasing (for positive Λ_i^τ) in the liquidation wedge. Higher liquidations result in a lower liquidation price (for positive Γ) due to more assets having to be absorbed by arbitrageurs (equation 19). These means that liquidations by intermediary i decrease in asset holdings and increase in the liquidation wedges applied to other intermediaries within the same sector and across different sectors (for positive matrix elements), a result of a substitution effect resulting from the increase in equilibrium price. In a model without fire sales, we have $\Lambda_j^{q,e} = \Lambda_j^{\tau,e} = 0$. We distinguish in equation 18 between the asset choices of intermediary i and the wedges applied to intermediary i's liquidations (denoted with no $*$) as opposed to equilibrium objects (denoted with $*$) that enter because they determine the equilibrium liquidation price.

Crucially, under the maintained information structure that private agents have a finer information partition than the regulator, the regulator's model choice can alter the endogenous portfolios q_i that feed into the determination of the equilibrium liquidations and liquidation prices through choice of the regulatory wedges, but not by changing the structural loadings (or agents' beliefs about them) $\Lambda_i = \{\Lambda_i^q, \Lambda_i^\tau, \Lambda_i^{q,e}, \Lambda_i^{\tau,e}\}$ that translate portfolio quantities and wedges into outcomes. In this sense, the equilibrium determination and the regulator's forecasting problem satisfy a key form of policy invariance.

5.2 Regulator's Optimal Wedges

We solve the regulator's problem by backward induction: first, we characterize the regulator's optimal intervention τ given a choice of model M and signal s. We then characterize the regulator's optimal choice of model M. To simplify analysis, we assume that the regulator places equal weight on all intermediaries but places a welfare weight of zero on arbitrageurs.[14]

Given that liquidation wedges are revenue-neutral, the regulator's optimal choice of τ solves

$$\max_\tau \mathbb{E}\left[\sum_i U_i \,|\, s, M\right] - \delta(\tau),$$

subject to equilibrium determination (Lemma 1).

As preliminaries to the proposition below, we define $\bar{\ell}_i(q) = \bar{\ell}_i + \Lambda_i^q q_i - \sum_i \Lambda_i^{q,e} q_i$ to be the liquidations of intermediary i if there is no regulatory intervention ($\tau = 0$). We define $L(q) = \sum_i \bar{\ell}_i(q)$ to be the $N \times 1$ vector capturing total liquidations of each asset if there is no intervention. The following proposition characterizes optimal liquidation wedges in terms of these objects and model parameters.

Proposition 1. *Given a model M and signal s, the regulator's optimal policy in the Middle is*

$$\tau^* = \mathbb{E}\left[\Xi \middle| s, M\right]^{-1} \mathbb{E}\left[(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma L(q) \middle| s, M\right] \tag{20}$$

where $\Xi = \overline{\Lambda}^{\tau T} + (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta$, where $\overline{\Lambda}_i^\tau = (e_i \otimes I_N)^T \Lambda_i^\tau - (\Lambda_1^{\tau,e}, \ldots, \Lambda_I^{\tau,e})$ is $N \times NI$ (where e_i is the standard basis vector whose i^{th} element is 1 and $\otimes$ is the Kronecker product), and where $\overline{\Lambda}^\tau = (\overline{\Lambda}_1^{\tau T}, \ldots, \overline{\Lambda}_I^{\tau T})^T$ is $NI \times NI$.

The optimal wedges of Proposition 1 are familiar from the macroprudential policy literature on fire sales, and intuitively encode an expected marginal cost-marginal benefit trade-off. The marginal cost of the policy is captured in the (conditional expectation of the) inverse matrix Ξ, while the marginal benefit is captured in the expectation.

There are three components to the private and regulatory marginal cost of liquidations, reflecting the distortion of intermediaries' activities away from their private optimum. First, increasing

[14] This focuses attention on a distributive externality from shifting wealth between arbitrageurs and intermediaries. This can be incorporated by assuming that arbitrageurs have a high marginal value of wealth in the Beginning but cannot borrow, meaning that Pareto improvements are achieved by raising the liquidation price in the Middle and having a lump sum transfer from intermediaries to arbitrageurs in the Beginning (see e.g., Clayton and Schaab 2025).

liquidation wedges directly distorts the intermediaries' activities (the first term of Ξ). Second, by using wedges to alter equilibrium prices, the regulator changes the incentives for intermediaries to sell different assets (the second term). Finally, there is the regulatory cost Δ.

The social marginal benefit of regulation arises from the mitigation of the fire sale. This has two components that are central to our analysis. First is the causal effect of the policy intervention on equilibrium liquidation prices, captured by the term $(\sum_i \overline{\Lambda}_i^{\tau})^T \Gamma$. The utility consequence of these price changes is proportional to the total value of assets being sold by intermediaries, $L(q)$.

Importantly, this means the social benefit of regulation derives from a product of the causal impact of the policy intervention, $(\sum_i \overline{\Lambda}_i^{\tau})^T \Gamma^T$, and the social value of changing the price, here given by $L(q)$. This means that in designing regulation, there is value not only to identifying causal policy impacts, but also to predicting the magnitude of liquidations $L(q)$. To fully disentangle these two mechanisms, we can assume independence of the predictive and causal components of the system.[15]

Definition 2 (Predictive-Causal Independence)**.** *We have predictive-causal independence if* $\{\Lambda_i^{\tau}\}$ *and* $\{\overline{\ell}_i, \Lambda_i^q, \Lambda_i^{q,e}\}$ *are independent of one another.*

Under predictive-causal independence, we obtain the following trivial corollary to Proposition 1

Corollary 1. *Under predictive-causal independence, the regulator's optimal wedges are*

$$\tau^* = \mathbb{E}\left[\Xi \middle| s, M\right]^{-1} \qquad \underbrace{\mathbb{E}\left[(\sum_i \overline{\Lambda}_i^{\tau})^T \Gamma \middle| s, M\right]}_{\text{Causal: Policy Impact on Liquidation Price}} \qquad \overbrace{\mathbb{E}\left[L(q) \middle| s, M\right]}^{\text{Predictive: Total Liquidations}} \tag{21}$$

An important implication of Proposition 1 and Corollary 1 is that a model that is purely predictive—that is, that can predict liquidations $L(q)$—can be valuable to a regulator, provided that the regulator has some prior or posterior knowledge over the causal impact of the policy. This causal component of the optimal policy rule could be obtained through a fully-specified equilibrium structural model (e.g., as reviewed in Christiano et al. 2005) or, under certain conditions, from causal effects that are estimated empirically in reduced form (Guren et al. 2021; McKay and Wolf 2023; Caravello et al. 2025). The predictive information informs the regulator as to the magnitude and margins for intervention by informing the regulator about the social benefit of the intervention. Corollary 1 implies that, holding fixed the causal impact of the policy, the regulator would design larger-magnitude interventions when the regulator's model predicted that total liquidations would be larger.

[15]Naturally absent this assumption, we could perform an analogous decomposition to Corollary 1, but also include the covariance between the two terms.

5.3 Expected Welfare from a Model and Optimal Model Choice

We next ask how a regulator in the Middle would choose a model $M \in \mathcal{M}$ under discretion, taking as given the asset holdings q of intermediaries. Because choice of model in turn impacts intermediaries' optimal portfolio allocations (see Section 5.6), we later consider model choice under commitment.

We begin by characterizing the expected utility to the regulator from a choice M of model, and then characterize optimal model choice. As a preliminary to the proposition below, we define $\theta_i(q) = R_i - (\overline{\gamma} - \Gamma L(q))$ to be the fire sale losses to intermediary i from selling assets prior to maturity in the event of no regulatory intervention. We define $\hat{L}(q) = \mathbb{E}[L(q)|s, M]$ to be predicted total liquidations, given a model M and signal s. For the presentation in the main text, we focus on the case assuming predictive-causal independence (Definition 2). The proof of Proposition 2 characterizes the general case.

Proposition 2. *Under predictive-causal independence, the regulator's ex-ante expected welfare given positions q and a model M is*

$$
\begin{aligned}
V(q, M) =& \mathbb{E}_0\left[q^T(R-p) - \ell(q)^T\theta(q) - \frac{1}{2}q^T H^q q - \frac{1}{2}\ell(q)^T H^\ell \ell(q)\right] \\
&+ \frac{1}{2}L_0(q)^T\Theta_0 L_0(q) + \frac{1}{2}\mathrm{tr}\Big(\Theta_0\, cov_0(\hat{L}(q))\Big),
\end{aligned}
\tag{22}
$$

where $\Theta_0 = \mathbb{E}_0[\Upsilon^T\Psi\Upsilon|M]$, *where* $\Psi = \mathbb{E}\left[2(\sum_i \overline{\Lambda}_i^\tau)^T\Gamma(\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \middle| s, M\right]$, *and where* $\Upsilon = \mathbb{E}\left[\Xi \middle| s, M\right]^{-1}\mathbb{E}\left[(\sum_i \overline{\Lambda}_i^\tau)^T\Gamma \middle| s, M\right]$.

Proposition 2 shows that the regulator's value function over assets q and the model M depends on two sets of terms.

The first line is the regulator's baseline welfare in the absence of intervention. Baseline welfare starts from the return on assets, $q^T(R-p)$, net of losses on assets sold prior to maturity, $-\ell(q)^T\theta(q)$. It then nets out the adjustment costs from the initial portfolio and from liquidations in the Middle. All of these terms are evaluated assuming no intervention, that is $\tau = 0$. As a result, they do not depend on the regulator's choice of model M.

The second line is the welfare gains resulting from the regulator's optimally chosen intervention, which comprises two terms. The first term reflects the expected magnitude and impact of the regulator's intervention. From Proposition 1 and Corollary 1, the intervention is determined by the predicted liquidations $L(q)$ and the causal impact of the policy intervention. Because interventions are targeted to the social benefit of intervening (equation 20), this term is therefore quadratic in the expected intervention and hence in ex-ante predicted liquidations $L_0(q)$. It is weighted by the consequences of intervention Θ_0, reflected by the extent to which interventions move prices (the first term in Ψ_0), the regulatory costs (the second term), and the movement in holding costs from liquidations.

The welfare also depends on the accuracy of the regulator's model and intervention, captured in the second term that depends on the covariance matrix of predicted liquidations, $cov_0(\hat{L}(q))$. The intuition comes from the law of total variance: a perfectly informed regulator would get an exact prediction of liquidations from observing the true parameters of the system, $\hat{L}(q) = L(q)$. A regulator that learned no information relative to the prior would have no covariance, so that all benefits would be reflected in the prior beliefs that are used to design the intervention.

In general, both of these terms depend on the choice of model M. The latter term depends on the choice of model because the choice of model determines the covariance matrix of the policy intervention. The former term also depends on the model, because the anticipated choice of model can affect the expected intervention. In particular, even under predictive-causal independence, from Proposition 1 a model that informs about the causal impact of the policy intervention τ will inform about both the costs Ξ of regulation and also about the causal impact $(\sum_i \overline{\Lambda}_i^{\tau})^T$ of the policy intervention. We define a *predictive* model as one that is uninformative about the causal structure of the policy intervention.

Definition 3. *We say a model M is* predictive *if $\mathbb{E}[\Xi|s, M] = \mathbb{E}_0[\Xi]$ and $\mathbb{E}[\overline{\Lambda}_i^{\tau}|s, M] = \mathbb{E}_0[\overline{\Lambda}_i^{\tau}]$ for all signals s.*

5.4 Optimal Predictive Model Choice

We can now characterize the optimal choice of a model. We maintain simplicity by assuming predictive-causal independence for the main text (Definition 2) and by focusing on predictive models (Definition 3).

We assume that the regulator faces a separable utility cost $\mathcal{C}(M, q)$ from adopting (predictive) model $M \in \mathcal{M}$. In Proposition 2, for a predictive model (Definition 3) the key sufficient statistic of the model from a welfare perspective is the prior covariance matrix over the ex-post prediction of liquidations, $\Sigma_0^{\hat{L}} = cov_0(\hat{L}(q))$. The matrix Θ_0 and the averaged expected liquidations $L_0(q)$ are invariant to model choice. For symmetric matrices $\Sigma_0^{\hat{L}}$ that are attainable from some model M, we can therefore re-represent costs as $C(\Sigma_0^{\hat{L}}, q) = \inf_{M \in \mathcal{M} | cov_0(\hat{L}(q)) = \Sigma_0^{\hat{L}}} \mathcal{C}(M, q)$. We assume that C is differentiable in $(\Sigma_0^{\hat{L}}, q)$ over an open ball that contains its optimal value.

As a result, for a predictive model we can write the regulator's optimization problem as

$$\max_{\Sigma_0^{\hat{L}}} \frac{1}{2} \mathrm{tr}\left(\Theta_0 \Sigma_0^{\hat{L}}\right) - C(\Sigma_0^{\hat{L}}, q)$$

subject to the constraint that $\Sigma_0^{\hat{L}}$ is a symmetric matrix. We obtain the following result on the optimal predictive model.

Proposition 3. *The regulator's optimal predictive model solves*

$$\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial \Sigma_0^{\hat{L}}} + \left(\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial \Sigma_0^{\hat{L}}}\right)^T = \Theta_0 \tag{23}$$

where $\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial \Sigma_0^{\hat{L}}}$ *is a square matrix whose ij-th element is* $\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial (\Sigma_0^{\hat{L}})_{ij}}$.

Proposition 3 yields an intuitive trade-off on optimal predictive model choice in terms of choice of covariance matrix of the policy intervention. The regulator is willing to pay a higher marginal cost to increase precision on dimensions where Θ_0 is larger, that is when the policy has greater impact on aggregate liquidations and prices, when the regulatory cost is higher, or when the impact through holding costs is higher. In this sense, there is a complementarity between predictive power and knowledge of the causal policy impact: the regulator is willing to pay larger costs to acquire precise predictions of aggregate liquidations precisely on dimensions on which the policy impact on liquidations and liquidation prices is anticipated to be largest.

5.5 Predictive Accuracy and Welfare

In Section 5.3, we showed that the welfare-relevant information for a predictive model is summarized by the prior covariance matrix over the ex-post policy interventions induced by the choice of that particular model. It is intuitive that this covariance matrix should relate to the predictive accuracy of the model, since it characterizes how well the intervention is targeted. In this section, we provide a corollary to Proposition 2 which formalizes this intuition, showing that the predictive correlation of a predictive model's forecasts—weighted appropriately according to the causal leverage of the policy—is a sufficient statistic for the welfare gains from the model.

To derive this corollary, we define a few objects. Given a square matrix W, we define variance and covariance operators that use W as a weighting matrix:

$$\mathrm{Cov}_W(X, Y) = \mathbb{E}\left[(X - E[X])^T W (Y - E[Y])\right], \quad \mathrm{Var}_W(X) = \mathrm{Cov}_W(X, X).$$

The maximum ex-ante expected welfare gain (relative to the no-intervention baseline) within the class of predictive models, $\Delta V_{\max}$, is attained by a perfect predictive signal—that is, a predictive model M whose forecasts $\widehat{L}(q) = \mathbb{E}[L(q) \mid s, M]$ satisfy $\widehat{L}(q) = L(q)$. The following corollary characterizes welfare losses relative to the perfect forecast benchmark $\Delta V_{\max}$ in terms of the model's predictive accuracy.

Corollary 2. *Under predictive-causal independence, the regulator's ex-ante expected welfare gain from a predictive model relative to the no-intervention baseline, given positions q and a model M is*

$$\Delta V(M) = \Delta V_{\max} \cdot \rho^2_{\Theta_0}(M), \tag{24}$$

where

$$\rho_{\Theta_0}(M) \equiv \frac{\text{Cov}_{\Theta_0}(L, \widehat{L})}{\sqrt{\text{Var}_{\Theta_0}(L)\,\text{Var}_{\Theta_0}(\widehat{L})}}, .$$

This result shows that the welfare gains from a predictive model scale linearly with the Θ_0-weighted R-squared achieved by the model in predicting liquidations. The weighting matrix Θ_0 has a natural interpretation as the metric that converts variation in predicted liquidations $\hat{L}(q)$ into variation in welfare after the regulator applies the optimal wedges τ^*: therefore, assets that generate larger externalities or for which the intervention has a higher causal leverage on outcomes receive a larger weight in the statistic $\rho_{\Theta_0}(M)$. The predictive R-squared has in fact an exact interpretation as the fraction of the maximum achievable welfare gain within the class of predictive models that is actually attained. This sufficient statistic provides a simple but direct way to quantify map the empirical performance of predictive models to welfare.

Corollary 2 completes the characterization of the regulator's ex-post problem. In Section 5.6, we study the equilibrium feedback of model choice and ex-post intervention on intermediaries' ex-ante portfolio decisions. The preceding empirical sections demonstrate that high-dimensional predictive models can deliver accurate cross-sectional forecasts of trading behavior—the targeting statistics that this framework suggests have welfare value.

5.6 Privately Optimal Asset Allocations

To examine how model choice and ex-post intervention shape the ex-ante asset allocations of intermediaries, we begin by studying the private optimum of individual intermediaries, and then study socially optimal interventions. Intermediary i in the Beginning takes as given the model choice M^* of the regulator and the resulting possible equilibria, and solves

$$\max_{q_i} \mathbb{E}_0\left[q_i^T(R_i - p_i) - \ell_i^T(R_i + \tau_i^* - \gamma) - \frac{1}{2}q_i^T H_i^q q_i - \frac{1}{2}\ell_i^T H_i^\ell \ell_i\right].$$

Intermediary i's asset allocation is therefore affected both through the specific intervention τ_i^* anticipated, and also through the liquidation price (which in turn also affects equilibrium liquidations). Intermediary i knows that equilibrium liquidations are determined as in Lemma 1, but only internalizes the effect of its own q_i on its own liquidations (and not on equilibrium liquidation price or equilibrium liquidations, and not on the optimal model choice or intervention).

We next turn to studying the effect of the regulator's model choice on ex-ante asset allocations of intermediaries. Note that Proposition 4 does not rely on predictive-causal independence or a predictive model.

Proposition 4. *The privately optimal asset allocation satisfies*

$$\mathbb{E}_0\left[H_i^q q_i^* + \Lambda_i^{qT} H_i^\ell \overline{\ell}_i(q^*)\right] = \mathbb{E}_0\left[R_i - p_i - \Lambda_i^{qT}\theta_i(q^*)\right] - \mathbb{E}_0\left[\Lambda_i^{qT}\left(\tau_i^* - \left(H_i^\ell \overline{\Lambda}_i^\tau + \Gamma(\sum_i \overline{\Lambda}_i^\tau)\right)\tau^*\right]\tag{25}$$

Proposition 4 expresses the optimal portfolio choice in the form of a marginal cost-marginal benefit trade-off. The left hand side captures the marginal cost of increasing holdings of an asset, which includes both the ex-ante and ex-post adjustment costs of holding more and liquidating more of an asset. This term is evaluated at the no-intervention benchmark, that is as-if we had $\tau^* = 0$.

The right hand side captures the marginal benefit, which is decomposed into a marginal benefit absent the ex-post regulatory intervention (the first term) plus the marginal benefit arising from the impact of intervention (the second term). The first term on the RHS is the baseline expected asset return, $R_i - p_i$, net of costs of liquidations. The liquidation costs are the amount liquidations are changed by increasing holdings, Λ_i^{qT}, times the fire sale loss in liquidation, $\theta_i(q^*)$.

The final term on the RHS captures the impacts of model choice and the ex-post intervention. This is the only term in equation 25 that depends on model choice and intervention. It captures the cost of holding an asset induced through regulation. The expectation of ex-post policy intervention has two impacts. First, a higher wedge τ_{in} on intermediary i increases the cost of liquidating asset n, discouraging the intermediary from holding portfolios that result in it liquidating that asset ex post. There are also equilibrium costs of the vector of wedges τ through the equilibrium price. In contrast, here a higher wedge τ_{in} encourages the intermediary i to hold more of an asset when the asset price rises as a result, which partially offsets the benefit from raising the price. This is a standard channel of moral hazard. This moral hazard channel is amplified when the regulator's instruments do not cover all holders of a given asset: unregulated intermediaries capture the benefit of higher liquidation prices without bearing any liquidation wedge, and so their ex-ante incentive to accumulate the asset is undeterred by the prospect of intervention.

It is clear that the ex-post intervention affects the optimal asset allocation: a higher expected tax on asset n ex post directly discourages its purchase ex ante, but a higher liquidation price ex post encourages its purchase ex ante. As a result, even a purely predictive model can impact the asset allocation ex ante. In particular, even though under a purely predictive model (Definition 3) the expectation of τ^* is that same as if the regulator ran no model, there is a covariance induced between the tax itself, τ^*, and the impact on liquidations, Λ_i^q, as long as the predictive model is loading at least some on Bayesian inference on the impact of asset holdings on liquidations Λ_i^q. That is to say, focusing on the direct term $\mathbb{E}_0[\Lambda_i^{qT}\tau_i^*]$, for a purely predictive model we can write

$$\mathbb{E}_0\left[\Lambda_i^{qT}\tau_i^*\right] = \mathbb{E}_0\left[\Lambda_i^{qT}\right]\mathbb{E}_0\left[\tau_i\right] + \mathrm{cov}_0\left(\Lambda_i^{qT}, \mathbb{E}_0[\Xi]^{-1}\mathbb{E}_0\left[(\sum_i \overline{\Lambda}_i^\tau)^T\Gamma\right]\mathbb{E}[L(q)|s, M]\right),$$

where the second term reflects how the true value of Λ_i^q varies with the prediction of liquidations.

In a similar fashion, moral hazard can also be exacerbated if the impact of asset allocations on liquidations Λ_i^q is what a key driver of the predictability of ex post liquidations.

More broadly, both the virtuous deterrence and the moral hazard channels are bounded by the precision of the regulator's model: a less granular model generates smaller covariance between the intervention and the structural loadings, and hence attenuates both the beneficial and the adverse feedback of the ex-post intervention on ex-ante portfolio choice.

5.7 Socially Optimal Asset Allocation

Finally, we study the constrained efficient asset allocation q of the regulator. Formally, we assume that the regulator can impose a wedge on asset holdings, that is a revenue-neutral tax $t_i = (t_{i1}, \ldots, t_{iN})^T$. Because the regulator has a complete set of wedges ex ante, this is equivalent to the regulator directly picking portfolio allocations ex ante.[16] The following proposition characterizes the optimal wedges $t = (t_1^T, \ldots, t_I^T)^T$ when the regulator chooses an optimal predictive model ex post.

Proposition 5. *For a predictive model, the social planer's optimal ex-ante portfolio wedges t are*

$$\begin{aligned} t =& \mathbb{E}_0\Big[(\sum_j \overline{\Lambda}_j^q)^T \Gamma L(q) - \Lambda^{q,eT} \sum_i \Big(\theta_i(q) + H_i^\ell \ell_i(q)\Big)\Big] \\ &+ \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq} - \mathbb{E}_0\Big[(\sum_i \overline{\Lambda}_i^q)^T\Big]\Theta_0 \mathbb{E}_0[L(q)] - \mathbb{E}_0\Big[\Psi\tau\Big] \end{aligned} \tag{26}$$

where $\mathbb{E}_0[\Psi\tau]$ is a stacked vector whose i^{th} block is $\mathbb{E}_0\Big[\Lambda_i^{qT}\Big(\tau_i - \Big(\Gamma(\sum_i \overline{\Lambda}_i^\tau) + H_i^\ell \overline{\Lambda}_i^\tau\Big)\tau\Big)\Big]$.

The optimal ex-ante asset tax formula is intuitive and is decomposed into two lines. The first line captures the uninternalized effects of intermediaries increasing holdings of an asset in absence of regulatory intervention. First, as q changes, total liquidations change across intermediaries, resulting in changes in the liquidation price and hence changes in revenue proceeds from total liquidations $L(q)$. Second, changes in forced liquidations through changes in the equilibrium price result in losses due to the size of the discount $\theta_i(q)$ and due to changes in marginal holding costs $H_i^\ell \ell_i(q)$. In absence of an ex-post intervention, this first line would capture the standard macroprudential regulation of asset positions.[17]

The second line captures the interaction of the ex-ante asset regulation with the ex-post model design and intervention. The first term, dC/dq, reflects how the changing assets held by intermediaries affects the cost of acquiring information through the model ex post. The regulator imposes

[16] It is straightforward to extend results to incomplete ex-ante instruments, but for brevity we focus on complete instruments.

[17] Since our framework allows negative positions $q_{in} < 0$, we can think of these negative positions as liabilities. As such, it also captures regulation of such liabilities.

larger holding taxes on asset positions that make running the model more costly ex post. For example, the regulator might discourage holdings of non-transparent or hard-to-assess asssets.

The second term on the second line captures the effect on the expected intervention size (the term $L_0(q)^T\Theta_0 L_0(q)$ in equation 22). Intuitively, concentrations into a position q increase total liquidations on the margin by $\sum_i \overline{\Lambda}_i^q$, which prompts a larger ex post intervention by the regulator. This increase in ex-post intervention helps to manage the fire sale and so mitigates the impact of the ex-ante increase in asset allocation. This gives a first dimension whereby the ex-post intervention provides a partial substitute for the ex-ante asset tax, and leads the regulator to require potentially smaller interventions ex ante, knowing that fire sales will be managed ex post.

Finally, there are the direct and moral hazard effects on intermediaries, $\mathbb{E}_0[\Psi\tau^*]$, are those in the final term in equation 25 of Proposition 4. First, the prospect of the ex-post tax on liquidations directly discourages holdings of the asset ex ante when holding more promotes liquidations ex post. Second, there is the moral hazard effect: as the liquidation price rises, intermediaries' perceived cost of liquidations $\theta_i(q)$ falls, and so they become more willing to hold more of an asset even if that forces them to liquidate. It is interesting again to observe that for assets for which the direct effect dominates the indirect price effect, the ex-post tax actually serves as a substitute for ex-ante regulation, leading to a smaller intervention t ex ante.

5.8 Ex-Post Subsidy-Based Interventions

Our baseline analysis assumes that the regulator directly manages liquidations through a wedge/tax on liquidations. In practice, ex-post interventions can also involve "bailout" interventions that subsidize retaining assets rather than taxing selling them (e.g. lender of last resort, debt guarantees). Suppose that rather than taxing liquidations ℓ_i, the regulator instead applies a subsidy on the amount $q_i - \ell_i$ of the asset that is held to maturity. Formally, the payoff to intermediary i in the End is now

$$U_i = U_i + (q_i^T - q_i^{*T})\tau_i - (\ell_i^T - \ell_i^{*T})\tau_i,$$

so that the regulator continues to apply revenue-neutral interventions.[18]

Because the regulator in the Middle takes the asset allocations as given, the regulator's optimization problem over both model choice and the ex-post intervention are formally the same as before. Thus, Lemma 1 and Propsitions 1-3 continue to apply. However, the privately optimal asset allocation is affected by the subsidy on asset retention. In particular, in Proposition 4, the expected return on holding asset q_i is raised from R_i to $R_i + \tau_i^*$. Intuitively an ex-post subsidy promotes overinvestment in that asset. This gives rise to a familiar channel of moral hazard.

Relative to the case of a liquidation tax, it is worthwhile to note that the only new term for private intermediaries in their optimization problem is the revenue benefits $q_i^T\mathbb{E}_0[\tau_i^*]$ of their

[18]Since individual intermediaries take revenue remissions as given, there is still moral hazard from the subsidy.

asset position. Therefore, relative to the liquidation tax, the regulator's model choice only affects intermediaries' asset allocation ex ante to the extent it changes the expected size of the intervention, $\mathbb{E}_0[\tau_i^*]$. In particular for a predictive model under predictive-causal independence (Definitions 2 and 3), we know that $\mathbb{E}_0[\tau_i^*]$ does not depend on the model used; instead, it is only the covariance matrix of the intervention (its precision) that deepends on the model. It is thus interesting and surprising that purely predictive models that help with prediction but not with causal inference do not exacerbate moral hazard relative to the case of the liquidation tax. In contrast, models that are informative about the causal impact of the policy intervention change expectations of the policy intervention, and are potentially associated with moral hazard. The logic is reminiscent of that of Laffont and Tirole (1986) in the context of regulation of a firm with unobservable effort and uncertain costs.

5.9 Extensions

Better Informed Intermediaries. Our model assumes that in the Beginning, intermediaries and regulators share a common prior over the model parameters. In practice, intermediaries may be better informed about model parameters. One could extend the model by assuming that intermediaries had a more precise prior than regulators. This would lead a regulator to also infer information about the structural parameters of the economy from observing portfolio holdings directly. One possible method of incorporating is to interpret $C(M, q)$ as a cost of the inference the regulator is undertaking, and so interpret the model as both a processing of information (including from such Bayesian inference). One possible advantage of the ex-post intervention would be its ability to react to information discovered from observing intermediaries' choices, which might reduce risks of moral hazard or imperfectly calibrated regulation ex ante. That is, better-informed intermediaries who saw a regulator was under-regulating an asset n ex ante would also know that the regulator would discover the mistake ex post, and so intervene more strongly upon it. Exploring the effects of differential information between the regulator and intermediaries is an interesting direction.

Dynamic Learning. We embed a one-shot learning problem. One could extend our framework to embed dynamic information acquisition by assuming that our baseline Beginning-Middle-End model was a stage game played at each date $t = 0, 1, \ldots$. In this environment, one could think of there being a true distribution μ^* from which model parameters are drawn each period, so that the regulator and intermediaries learn about this true distribution over time. The regulator and intermediaries would carry information forward at each date, and so the regulator would consider both how a model acquired information on the current crisis and also how it informed about the underlying variables. We conjecture that this would make predictive models relatively myopically useful: they would give potentially substantial information for intervening in the current crisis, but relatively little information about the underlying structural parameters, and so might be of limited use in updating beliefs about the true distribution of parameters. This could face the regulator with an interesting dynamic trade-off between myopically acquiring more predictive information, and trying to uncover the true structural parameters that would also be useful for designing regulation and interventions during the next crisis.

Commitment vs. Discretion in Model Choice. We have assumed the regulator chooses the model and ex-post policy intervention with discretion, after asset allocations are chosen. As highlighted by the results in Section 5.6, this leads to a potential time consistency problem in model choice since the model choice affects ex-ante asset allocations. This time consistency problem will likely be more pronounced the more incomplete the regulator's ability to regulate portfolio positions is ex ante, for example if the regulator cannot regulate all intermediaries or all assets. We leave the implications of commitment versus discretion for optimal model design to future work.

6 Conclusion

This paper introduces a graph-based deep learning architecture for institutional holdings data and demonstrates that it substantially improves the measurement of financial fragility. We complement these empirical contributions with a theoretical framework that clarifies how predictive models can improve regulation. The graph transformer learns latent representations of investors and assets that deliver strong out-of-sample conditional forecasts of trading behavior, including during crisis episodes, and that explain the cross-section of asset price dislocations during stress events. These forecasts provide a practical way to estimate the sufficient statistics that the theory identifies as governing cross-sectional policy targeting, and our analysis demonstrates that real-time prediction of portfolio dynamics is feasible. While predictive models are not substitutes for structural analysis or causal inference, our results indicate that they can be powerful complements when regulators have targeted instruments and credible knowledge of policy transmission.

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Online Appendix for
"Financial Regulation and AI: A Faustian Bargain?"

Christopher Clayton Antonio Coppola

March 2026

A Proofs

A.1 Proof of Lemma 1

Intermediary i's Lagrangian over ℓ_i is

$$\mathcal{L}_i = q_i^T(R_i - p_i) - \ell_i^T(R_i + \tau_i - \gamma) - \frac{1}{2}q_i^T H_i^q q_i - \frac{1}{2}\ell_i^T H_i^\ell \ell_i - \lambda_i^T(A_i^\ell \ell_i - A_i^q q_i - \rho_i),$$

yielding FOCs

$$0 = -(R_i + \tau_i - \gamma) - H_i^\ell \ell_i - A_i^{\ell T}\lambda_i,$$

$$\ell_i = -H_i^{\ell-1}(R_i + \tau_i - \gamma) - H_i^{\ell-1}A_i^{\ell T}\lambda_i.$$

Assuming the rollover constraint binds,

$$A_i^\ell\Big[-H_i^{\ell-1}(R_i + \tau_i - \gamma) - H_i^{\ell-1}A_i^{\ell T}\lambda_i\Big] = A_i^q q_i + \rho_i,$$

$$-\lambda_i = (A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^\ell H_i^{\ell-1}(R_i + \tau_i - \gamma) + (A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^q q_i + (A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}\rho_i,$$

and so we have

$$\begin{aligned}\ell_i = {} & H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}\rho_i + H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^q q_i \\ & + \Big[H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^\ell H_i^{\ell-1} - H_i^{\ell-1}\Big](R_i + \tau_i - \gamma).\end{aligned}$$

We therefore write

$$\ell_i = \overline{\ell}_i^0 + \Lambda_i^q q_i - \Lambda_i^\tau(\tau_i - \gamma),$$

where

$$\overline{\ell}_i^0 = H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}\rho_i - \Lambda_i^\tau R_i,$$

$$\Lambda_i^q = H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^q,$$

$$\Lambda_i^\tau = H_i^{\ell-1} - H_i^{\ell-1}A_i^{\ell T}(A_i^\ell H_i^{\ell-1}A_i^{\ell T})^{-1}A_i^\ell H_i^{\ell-1}.$$

Arbitrageur maximization yields

$$\gamma = \overline{\gamma} - \Gamma L,$$

$$\gamma = \overline{\gamma} - \Gamma \sum_i \overline{\ell}_i^0 - \Gamma \sum_i \Lambda_i^q q_i + \Gamma \sum_i \Lambda_i^\tau (\tau_i - \gamma),$$

$$\gamma = \left(\mathbb{I} + \Gamma \sum_i \Lambda_i^\tau\right)^{-1} \left(\overline{\gamma} - \Gamma \sum_i \overline{\ell}_i^0\right) - \sum_i \left[\left(\mathbb{I} + \Gamma \sum_i \Lambda_i^\tau\right)^{-1} \Gamma \Lambda_i^q q_i - \left(\mathbb{I} + \Gamma \sum_i \Lambda_i^\tau\right)^{-1} \Gamma \Lambda_i^\tau \tau_i\right],$$

$$\gamma = \overline{\gamma}^e - \Gamma^e \sum_i \left[\Lambda_i^q q_i^* - \Lambda_i^\tau \tau_i^*\right],$$

where we have defined $\overline{\gamma}^e = \left(\mathbb{I} + \Gamma \sum_i \Lambda_i^\tau\right)^{-1} \left(\overline{\gamma} - \Gamma \sum_i \overline{\ell}_i^0\right)$ and $\Gamma^e = \left(\mathbb{I} + \Gamma \sum_i \Lambda_i^\tau\right)^{-1} \Gamma$. Finally substituting back in,

$$\ell_i = \overline{\ell}_i + \Lambda_i^q q_i - \Lambda_i^\tau \tau_i - \sum_i \left[\Lambda_i^{q,e} q_i^* - \Lambda_i^{\tau,e} \tau_i^*\right],$$

where $\overline{\ell}_i = \overline{\ell}_i^0 + \Lambda_i^\tau \overline{\gamma}^e$, $\Lambda_i^{q,e} = \Lambda_i^\tau \Gamma^e \Lambda_i^q$, and $\Lambda_i^{\tau,e} = \Lambda_i^\tau \Gamma^e \Lambda_i^\tau$.

A.2 Proof of Proposition 1

From Lemma 1, equilibrium liquidations given (q, τ) are

$$\ell_i = \overline{\ell}_i + \Lambda_i^q q_i - \Lambda_i^\tau \tau_i - \sum_i \left[\Lambda_i^{q,e} q_i - \Lambda_i^{\tau,e} \tau_i\right].$$

We define $\overline{\Lambda}_i^\tau = (e_i \otimes I_N)^T \Lambda_i^\tau - (\Lambda_1^{\tau,e}, \ldots, \Lambda_I^{\tau,e})$ (where e_i is the standard basis vector whose i^{th} element is 1 and $\otimes$ is the Kronecker product) and similarly define $\overline{\Lambda}_i^q = (e_i \otimes I_N)^T \Lambda_i^q q_i - (\Lambda_1^{q,e}, \ldots, \Lambda_I^{q,e})$. We then write

$$\ell_i = \overline{\ell}_i + \overline{\Lambda}_i^q q - \overline{\Lambda}_i^\tau \tau.$$

Stacking over i, we have

$$\ell = \overline{\ell} + \overline{\Lambda}^q q - \overline{\Lambda}^\tau \tau.$$

Next, we can write the regulator's objective as

$$\mathbb{E}\left[\sum U_i - \delta(\tau) \middle| s, M\right] = \mathbb{E}\left[\sum_i \mathcal{L}_i \middle| s, M\right] + \mathbb{E}\left[\tau^T \ell \middle| s, M\right] - \frac{1}{2}\tau^T \Delta \tau,$$

where as in the proof of Lemma 1 we have defined the intermediary i Lagrangian by

$$\mathcal{L}_i = q_i^T (R_i - p_i) - \ell_i^T (R_i + \tau_i - \gamma) - \frac{1}{2} q_i^T H_i^q q_i - \frac{1}{2} \ell_i^T H_i^\ell \ell_i - \lambda_i^T (A_i^\ell \ell_i - A_i^q q_i - \rho_i).$$

The regulator thus solves

$$\max_\tau \mathbb{E}\left[\sum_i \mathcal{L}_i \middle| s, M\right] + \mathbb{E}\left[\tau^T \ell \middle| s, M\right] - \frac{1}{2}\tau^T \Delta \tau$$

subject to

$$\ell = \overline{\ell} + \overline{\Lambda}^q q - \overline{\Lambda}^\tau \tau,$$

$$\gamma = \overline{\gamma} - \Gamma L.$$

By the Envelope Theorem, we have the regulator's FOC given by

$$0 = \mathbb{E}\Big[- \ell + \sum_i \ell_i \frac{\partial \gamma}{\partial \tau}\Big| s, M\Big] + \mathbb{E}\Big[\frac{\partial \tau^T \ell}{\partial \tau}\Big| s, M\Big] - \Delta\tau,$$

$$0 = \mathbb{E}\Big[\sum_i (\overline{\Lambda}_i^\tau)^T \Gamma^T L \Big| s, M\Big] + \mathbb{E}\Big[- \overline{\Lambda}^{\tau T} \tau \Big| s, M\Big] - \Delta\tau.$$

Writing $L = L(q) - \sum_i (\overline{\Lambda}_i^\tau)\tau$ and using the assumption that Γ is symmetric,

$$\mathbb{E}[\overline{\Lambda}^{\tau T} | s, M] + \Delta\tau = \mathbb{E}\Big[\sum_i (\overline{\Lambda}_i^\tau)^T \Gamma \Big(L(q) - \sum_i (\overline{\Lambda}_i^\tau)\tau\Big)\Big| s, M\Big],$$

$$\tau = \mathbb{E}\Big[\Xi\Big| s, M\Big]^{-1} \mathbb{E}\Big[(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma L(q)\Big| s, M\Big],$$

where $\Xi = \overline{\Lambda}^{\tau T} + (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma^T (\sum_i \overline{\Lambda}_i^\tau) + \Delta$.

A.3 Proof of Proposition 2

As in the proof of Proposition 1, the regulator's ex-ante expected welfare given positions q, a model M, and a signal s is

$$V(q, M, s) = \mathbb{E}\Big[q^T(R - p) - \frac{1}{2} q^T H^q q \Big| s, M\Big] + \mathbb{E}\Big[\sum_i \Big[- \ell_i^T (R_i - \gamma) - \frac{1}{2}\ell_i^T H_i^\ell \ell_i\Big] - \frac{1}{2}\tau^T \Delta \tau \Big| s, M\Big],$$

where we define H^q to be the block diagonal matrix whose diagonal elements are H_i^q. We define $\theta_i(q) = R_i - \overline{\gamma} + \Gamma L(q)$ to obtain:

$$V(q, M, s) = \mathbb{E}\Big[q^T(R - p) - \frac{1}{2} q^T H^q q \Big| s, M\Big] + \mathbb{E}\Big[- \ell^T \theta(q) + L^T \Gamma \sum_i (\overline{\Lambda}_i^\tau)\tau - \frac{1}{2}\ell_i^T H_i^\ell \ell_i - \frac{1}{2}\tau^T \Delta \tau \Big| s, M\Big],$$

$$\begin{aligned} V(q, M, s) = {} & \mathbb{E}\Big[q^T(R - p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) \Big| s, M\Big] + \mathbb{E}\Big[\tau^T \overline{\Lambda}^{\tau T} \theta(q) \\ & + \tau^T (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma \Big(L(q) - (\sum_i \overline{\Lambda}_i^\tau)\tau\Big) - \frac{1}{2}\ell_i^T H_i^\ell \ell_i - \frac{1}{2}\tau^T \Delta \tau \Big| s, M\Big], \end{aligned}$$

$$\begin{aligned} V(q, M, s) = {} & \mathbb{E}\Big[q^T(R - p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) \Big| s, M\Big] + \mathbb{E}\Big[\tau^T \Big(\overline{\Lambda}^{\tau T} \theta(q) \\ & + (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma L(q)\Big) - \tau^T \Big((\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \frac{1}{2}\Delta\Big)\tau - \frac{1}{2}\ell^T H^\ell \ell \Big| s, M\Big]. \end{aligned}$$

From here, we can expand out

$$\ell^T H^\ell \ell = \left(\ell(q)^T - \tau^T \overline{\Lambda}^{\tau T}\right) H^\ell \left(\ell(q) - \overline{\Lambda}^\tau \tau\right) = \ell(q)^T H^\ell \ell(q) - 2\tau^T \overline{\Lambda}^{\tau T} H^\ell \ell(q) + \tau^T \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \tau,$$

and substitute back in to obtain

$$\begin{aligned} V(q, M, s) = \mathbb{E}\Big[& q^T(R-p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q) \Big| s, M\Big] \\ &+ \mathbb{E}\Big[\tau^T \Big(\overline{\Lambda}^{\tau T}\theta(q) + (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma L(q) + \overline{\Lambda}^{\tau T} H^\ell \ell(q)\Big) \\ &- \frac{1}{2}\tau^T\Big(2(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau\Big)\tau \Big| s, M\Big]. \end{aligned}$$

Note that this welfare function is necessarily equivalent to that obtained in Proposition 1. Therefore, an optimal tax formula that is equivalent to that in Proposition 1 yields:

$$\tau = \mathbb{E}\Big[2(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \Big| s, M\Big]^{-1} \mathbb{E}\Big[\overline{\Lambda}^{\tau T}\theta(q) + (\sum_i \overline{\Lambda}_i^\tau)^T \Gamma L(q) + \overline{\Lambda}^{\tau T} H^\ell \ell(q) \Big| s, M\Big].$$

Accordingly substituting back into welfare, we have

$$\begin{aligned} V(q, M, s) =& \mathbb{E}\Big[q^T(R-p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q) \Big| s, M\Big] \\ &+ \frac{1}{2}\tau^T \mathbb{E}\Big[2(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \Big| s, M\Big]\tau. \end{aligned}$$

We can then characterize the expected welfare gains by

$$\begin{aligned} V(q, M) =& \mathbb{E}_0\Big[q^T(R-p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q) \Big| M\Big] \\ &+ \frac{1}{2}\mathbb{E}_0\Big[\tau^T \mathbb{E}\Big[2(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \Big| s, M\Big]\tau \Big| M\Big], \end{aligned}$$

where τ is given as in Proposition 1.

From here, we define $\Psi = \mathbb{E}\Big[2(\sum_i \overline{\Lambda}_i^\tau)^T \Gamma (\sum_i \overline{\Lambda}_i^\tau) + \Delta + \overline{\Lambda}^{\tau T} H^\ell \overline{\Lambda}^\tau \Big| s, M\Big]$, and note that $\Psi^T = \Psi$. We can then write more compactly,

$$\begin{aligned} V(q, M) =& \mathbb{E}_0\Big[q^T(R-p) - \frac{1}{2} q^T H^q q - \ell(q)^T \theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q) \Big| M\Big] \\ &+ \frac{1}{2}\mathbb{E}_0\Big[\tau^T \Psi \tau \Big| M\Big]. \end{aligned}$$

Predictive-Causal Independence. Under predictive-causal independence, we have

$$\tau^* = \mathbb{E}\left[\Xi\middle|s,M\right]^{-1}\mathbb{E}\left[(\sum_i \overline{\Lambda}_i^\tau)^T\Gamma\middle|s,M\right]\mathbb{E}\left[L(q)\middle|s,M\right].$$

We therefore define $\Upsilon = \mathbb{E}\left[\Xi\middle|s,M\right]^{-1}\mathbb{E}\left[(\sum_i \overline{\Lambda}_i^\tau)^T\Gamma\middle|s,M\right]$ and define $\Theta = \Upsilon^T\Psi\Upsilon$. Then, defining $\hat{L}(q) = \mathbb{E}[L(q)|s,M]$ to be predicted liquidations, we have:

$$\begin{aligned} V(q,M) =& \mathbb{E}_0\left[q^T(R-p) - \frac{1}{2}q^T H^q q - \ell(q)^T\theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q)\middle|M\right] \\ &+ \frac{1}{2}\mathbb{E}_0\left[\hat{L}(q)^T\Theta\hat{L}(q)\middle|M\right]. \end{aligned}$$

Using predictive-causal independence, we have:

$$\begin{aligned} V(q,M) = \mathbb{E}_0&\left[q^T(R-p) - \frac{1}{2}q^T H^q q - \ell(q)^T\theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q)\middle|M\right] \\ &+ \frac{1}{2}\mathbb{E}_0\left[\hat{L}(q)^T\Theta_0\hat{L}(q)\middle|M\right]. \end{aligned}$$

Finally, expanding the second line, we obtain

$$\begin{aligned} V(q,M) =& \mathbb{E}_0\left[q^T(R-p) - \frac{1}{2}q^T H^q q - \ell(q)^T\theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q)\middle|M\right] \\ &+ \frac{1}{2}L_0(q)^T\Theta_0 L(q) + \frac{1}{2}\mathrm{tr}(\Theta_0 cov_0(\hat{L}(q))). \end{aligned}$$

A.4 Proof of Proposition 3

The optimal model choice solves

$$\max_{\Sigma_0^{\hat{L}}} \frac{1}{2}\mathrm{tr}\left(\Theta_0\Sigma_0^{\hat{L}}\right) - C(\Sigma_0^{\hat{L}}, q)$$

subject to the restriction that $\Sigma_0^{\hat{L}}$ is symmetric. Taking the first order condition, we have

$$\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial \Sigma_0^{\hat{L}}} + \left(\frac{\partial C(\Sigma_0^{\hat{L}}, q)}{\partial \Sigma_0^{\hat{L}}}\right)^T = \Theta_0$$

since Θ_0 is symmetric.

A.5 Proof of Proposition 4

The intermediary i ex ante optimization problem is

$$\max_{q_i} \mathbb{E}_0\Bigg[\sum_i \Bigg[q_i^T(R_i - p_i) - \ell_i^T(R_i + \tau_i^* - \gamma) - \frac{1}{2}q_i^T H_i^q q_i - \frac{1}{2}\ell_i^T H_i^\ell \ell_i\Bigg]\Bigg],$$

where we have

$$\ell_i = \overline{\ell}_i + \Lambda_i^q q_i - \sum_j \Lambda_j^{q,e} q_j^* - \overline{\Lambda}_i^\tau \tau^*.$$

So, we have the FOC

$$0 = \mathbb{E}_0\Bigg[R_i - p_i - \Lambda_i^{qT}(R_i + \tau_i^* - \gamma) - H_i^q q_i - \Lambda_i^{qT} H_i^\ell \ell_i\Bigg].$$

Substituting in for ℓ_i, we have

$$\mathbb{E}_0\Bigg[H_i^q\Bigg]q_i = \mathbb{E}_0\Bigg[R_i - p_i - \Lambda_i^{qT}(R_i + \tau_i^* - \gamma) - \Lambda_i^{qT} H_i^\ell\Bigg(\overline{\ell}_i + \Lambda_i^q q_i - \sum_j \Lambda_j^{q,e} q_j^* - \overline{\Lambda}_i^\tau \tau^*\Bigg)\Bigg],$$

$$\mathbb{E}_0\Bigg[H_i^q + \Lambda_i^{qT} H_i^\ell \Lambda_i^q\Bigg]q_i = \mathbb{E}_0\Bigg[R_i - p_i - \Lambda_i^{qT}(R_i - \gamma) - \Lambda_i^{qT} H_i^\ell\Bigg(\overline{\ell}_i - \sum_j \Lambda_j^{q,e} q_j^*\Bigg)\Bigg] + \mathbb{E}_0\Bigg[-\Lambda_i^{qT}\tau_i^* + \Lambda_i^{qT} H_i^\ell \overline{\Lambda}_i^\tau \tau^*\Bigg].$$

We use that $R_i - \gamma = \theta_i(q^*) - \Gamma(\sum_i \overline{\Lambda}_i^\tau)\tau^*$ to obtain

$$\mathbb{E}_0\Bigg[H_i^q q_i^* + \Lambda_i^{qT} H_i^\ell \overline{\ell}_i(q^*)\Bigg] = \mathbb{E}_0\Bigg[R_i - p_i - \Lambda_i^{qT}\theta_i(q^*)\Bigg] - \mathbb{E}_0\Bigg[\Lambda_i^{qT}\Bigg(\tau_i^* - \Bigg(H_i^\ell \overline{\Lambda}_i^\tau + \Lambda_i^{qT}\Gamma(\sum_i \overline{\Lambda}_i^\tau)\Bigg)\tau^*\Bigg].$$

A.6 Proof of Proposition 5

We have that:

$$\begin{aligned} V(q, M) = \mathbb{E}\Bigg[q^T(R - p) - \frac{1}{2}q^T H^q q - \ell(q)^T\theta(q) - \frac{1}{2}\ell(q)^T H^\ell \ell(q)\Bigg] \\ + \frac{1}{2}L_0(q)\Theta_0 L_0(q) + \frac{1}{2}\mathrm{tr}(\Theta_0 cov_0(\hat{L}(q)). \end{aligned}$$

Recalling that $\ell_i(q) = \overline{\ell}_i + \overline{\Lambda}_i^q q$, $\theta_i(q) = R_i - \overline{\gamma} + \Gamma L(q)$, and $L(q) = \sum_i \overline{\ell}_i + \sum_i \overline{\Lambda}_i^q q$, then we can expand:

$$\sum_i \ell_i(q)^T\theta_i(q) = \sum_i \overline{\ell}_i^T\theta_i(0) + q^T\sum_i \overline{\Lambda}_i^{qT}\theta_i(0) + q^T(\sum_j \overline{\Lambda}_j^q)^T\Gamma L(0) + q^T\sum_i\Bigg(\overline{\Lambda}_i^{qT}\Bigg)\Bigg(\Gamma\sum_j \overline{\Lambda}_j^q\Bigg)q,$$

$$\ell(q)H^\ell\ell(q) = \sum_i \overline{\ell}_i^T H_i^\ell \overline{\ell}_i + 2q^T\Bigg(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\ell}_i\Bigg) + q^T\Bigg(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\Lambda}_i^q\Bigg)q.$$

For a predictive model, Θ_0 is invariant to the model choice M and to q. Therefore by the

Envelope Theorem,

$$0 = \mathbb{E}_0 \Bigg[R - p - H^q q - \Bigg[\sum_i \overline{\Lambda}_i^{qT} \theta_i(0) + (\sum_j \overline{\Lambda}_j^q)^T \Gamma L(0)$$
$$+ 2 \sum_i \Big(\overline{\Lambda}_i^{qT} \Big) \Big(\Gamma \sum_j \overline{\Lambda}_j^q \Big) q \Bigg] - \Bigg[\Big(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\ell}_i \Big) + \Big(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\Lambda}_i^q \Big) q \Bigg] \Bigg]$$
$$- \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq} + \mathbb{E}_0 \Big[(\sum_i \overline{\Lambda}_i^q)^T \Big] \Theta_0 \mathbb{E}_0 [L(q)],$$

$$0 = \mathbb{E}_0 \Bigg[R - p - H^q q - \Bigg[\sum_i \overline{\Lambda}_i^{qT} \Bigg(\theta_i(0) + \Big(\Gamma \sum_j \overline{\Lambda}_j^q \Big) q \Bigg) + (\sum_j \overline{\Lambda}_j^q)^T \Gamma \Big(L(0) + \sum_j \overline{\Lambda}_j^q q \Big) \Bigg]$$
$$- \Bigg[\Big(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\ell}_i \Big) + \Big(\sum_i \overline{\Lambda}_i^{qT} H_i^\ell \overline{\Lambda}_i^q \Big) q \Bigg] \Bigg] - \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq}$$
$$+ \mathbb{E}_0 \Big[(\sum_i \overline{\Lambda}_i^q)^T \Big] \Theta_0 \mathbb{E}_0 [L(q)] \,.$$

We have

$$\theta_i(0) + \Gamma \Big(\sum_j \overline{\Lambda}_j^q \Big) q = \theta_i(q),$$

$$L(0) + \Big(\sum_j \overline{\Lambda}_j^q \Big) q = L(q),$$

so we get:

$$\mathbb{E}_0 \Big[H^q q \Big] = \mathbb{E}_0 \Big[R - p - \sum_i \overline{\Lambda}_i^{qT} \Big(\theta_i(q) + H_i^\ell \ell_i(q) \Big) \Big] - \mathbb{E}_0 \Big[(\sum_j \overline{\Lambda}_j^q)^T \Gamma L(q) \Big]$$
$$- \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq} + \mathbb{E}_0 \Big[(\sum_i \overline{\Lambda}_i^q)^T \Big] \Theta_0 \mathbb{E}_0 [L(q)].$$

Recall that we have

$$\ell_i(q) = \overline{\ell}_i + \Lambda_i^q q_i - \sum_j \Lambda_j^{q,e} q_{ij},$$

then

$$\sum_i \overline{\Lambda}_i^{qT} \Big(\theta_i(q) + H_i^\ell \ell_i(q) \Big) = \Lambda^{qT} \Big(\theta(q) + H^\ell \ell(q) \Big) - \sum_i (\Lambda_1^{q,e}, \ldots, \Lambda_I^{q,e})^T \Big(\theta_i(q) + H_i^\ell \ell_i(q) \Big),$$

so we can then write

$$\mathbb{E}_0 \Big[H^q q \Big] = \mathbb{E}_0 \Big[R - p - \Lambda^{qT} \Big(\theta(q) + H^\ell \ell(q) \Big) \Big] + \mathbb{E}_0 \Big[\sum_i (\Lambda_1^{q,e}, \ldots, \Lambda_I^{q,e})^T \Big(\theta_i(q)$$
$$+ H_i^\ell \ell_i(q) \Big) - (\sum_j \overline{\Lambda}_j^q)^T \Gamma L(q) \Big] - \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq} + \mathbb{E}_0 \Big[(\sum_i \overline{\Lambda}_i^q)^T \Big] \Theta_0 \mathbb{E}_0 [L(q)].$$

Now, recall that we can write the private FOC, subject to an ex-ante asset tax t_i, as

$$\mathbb{E}_0\left[H_i^q\right]q_i = \mathbb{E}_0\left[R_i - (p_i + t_i) - \Lambda_i^{qT}\Big(\theta_i(q^*) + H_i^\ell \ell_i(q)\Big)\right] - \mathbb{E}_0\left[\Lambda_i^{qT}\Big(\tau_i - \Big(\Gamma(\sum_i \overline{\Lambda}_i^\tau) + H_i^\ell \overline{\Lambda}_i^\tau\Big)\tau\Big)\right].$$

Therefore, stacking and combining the two equations we obtain:

$$\begin{aligned}-t - \mathbb{E}_0\left[\Psi\tau\right] = \mathbb{E}_0\bigg[&\sum_i (\Lambda_1^{q,e}, \ldots, \Lambda_I^{q,e})^T\Big(\theta_i(q) + H_i^\ell \ell_i(q)\Big) \\ &- (\sum_j \overline{\Lambda}_j^q)^T \Gamma L(q)\bigg] - \frac{dC(\Sigma_0^{\hat{L}}, q)}{dq} + \mathbb{E}_0\left[(\sum_i \overline{\Lambda}_i^q)^T\right]\Theta_0 \mathbb{E}_0[L(q)],\end{aligned}$$

where $\mathbb{E}_0\left[\Psi\tau\right]$ is the stacking of $\mathbb{E}_0\left[\Lambda_i^{qT}\Big(\tau_i - \Big(\Gamma(\sum_i \overline{\Lambda}_i^\tau) + H_i^\ell \overline{\Lambda}_i^\tau\Big)\tau\Big)\right]$. Thus defining $\Lambda^{q,e} = (\Lambda_1^{q,e}, \ldots, \Lambda_I^{q,e})$, we have

$$t = \mathbb{E}_0\left[(\sum_j \overline{\Lambda}_j^q)^T \Gamma L(q) - \Lambda^{q,eT} \sum_i \Big(\theta_i(q) + H_i^\ell \ell_i(q)\Big)\right].$$

A.7 Proof of Corollary 2

From Proposition 2, the welfare gain of a predictive model relative to using just the prior is:

$$\Delta V = \frac{1}{2}\,\mathrm{tr}(\Theta_0\,\mathrm{cov}(\widehat{L})).$$

The maximum welfare gain within the class of predictive models is attained by a perfect predictive signal ($\widehat{L} = L$), so:

$$\Delta V_{\max} = \frac{1}{2}\,\mathrm{tr}(\Theta_0\,\mathrm{cov}(L)).$$

Define variance and covariance operators that use S as a weighting matrix:

$$\mathrm{Var}_S(X) := \mathbb{E}\left[(X - E[X])^T S (X - E[X])\right],$$

$$\mathrm{Cov}_S(X, Y) := \mathbb{E}\left[(X - E[X])^T S (Y - E[Y])\right].$$

Then the S-weighted correlation between the predictions $\widehat{L}$ and the true liquidations L is:

$$\rho_S \equiv \frac{\mathrm{Cov}_S(L, \widehat{L})}{\sqrt{\mathrm{Var}_S(L)\,\mathrm{Var}_S(\widehat{L})}}.$$

For S deterministic and since $\mathbb{E}L = \mathbb{E}\widehat{L}$ by the law of iterated expectations, we have that:

$$\mathrm{Cov}_S(L, \widehat{L}) := \mathbb{E}\left[(L - \mathbb{E}L)^T S(\widehat{L} - \mathbb{E}L)\right] = \mathbb{E}\left[(\mathbb{E}[L \mid s] - \mathbb{E}L)^T S(\mathbb{E}[L \mid s] - \mathbb{E}L)\right] = \mathrm{Var}_S(\widehat{L}).$$

Therefore:

$$\rho_S^2 = \frac{\mathrm{Var}_S(\widehat{L})^2}{\mathrm{Var}_S(\widehat{L})\,\mathrm{Var}_S(L)} = \frac{\mathrm{Var}_S(\widehat{L})}{\mathrm{Var}_S(L)}.$$

Using the fact that $\mathrm{Var}_S(X) = \mathbb{E}\left[(X - \mathbb{E}[X])^T S (X - \mathbb{E}[X])\right] = \mathrm{tr}(S\,\mathrm{cov}(X))$, we then have that:

$$\rho_S^2 = \frac{\mathrm{tr}(S\,\mathrm{cov}(\widehat{L}))}{\mathrm{tr}(S\,\mathrm{cov}(L))}.$$

Therefore, $\Delta V = \Delta V_{\max} \cdot \rho_{\Theta_0}^2$.

B Architecture and Training Details

This appendix provides the detailed specifications deferred from Section 3.

Multi-Head Attention Computation. We allow for S_A distinct and independent attention heads. For each head $s \in \{1, \ldots, S_A\}$, we compute query, key, and value projections using learnable projection matrices $W_q^{(\ell,s)}, W_k^{(\ell,s)} \in \mathbb{R}^{d_k \times d_h}$ and $W_v^{(\ell,s)} \in \mathbb{R}^{d_v \times d_h}$, where $d_k = d_v = d_h/S_A$. Define

$$Q_{v,t}^{(\ell,s)} = W_q^{(\ell,s)} h_{v,t}^{(\ell-1)}, \qquad K_{u,t}^{(\ell,s)} = W_k^{(\ell,s)} h_{u,t}^{(\ell-1)}, \qquad V_{u,t}^{(\ell,s)} = W_v^{(\ell,s)} M_{u,t}^{(\ell)}. \tag{A.1}$$

For each edge (v, u), attention weights are formed by a neighborhood softmax, incorporating the normalized edge exposure $\tilde{w}_{vu,t}$ as an additive log-bias:

$$\alpha_{vu,t}^{(\ell,s)} = \frac{\exp\left(\frac{\left(Q_{v,t}^{(\ell,s)}\right)^T K_{u,t}^{(\ell,s)}}{\sqrt{d_k}} + \log \tilde{w}_{vu,t}\right)}{\sum_{u' \in \mathcal{N}_t(v)} \exp\left(\frac{\left(Q_{v,t}^{(\ell,s)}\right)^T K_{u',t}^{(\ell,s)}}{\sqrt{d_k}} + \log \tilde{w}_{vu',t}\right)}. \tag{A.2}$$

This ensures $\sum_{u \in \mathcal{N}_t(v)} \alpha_{vu,t}^{(\ell,s)} = 1$ for each head and node. The aggregated message for each node is

$$m_{v,t}^{(\ell,s)} = \sum_{u \in \mathcal{N}_t(v)} \alpha_{vu,t}^{(\ell,s)}\, V_{u,t}^{(\ell,s)}, \qquad m_{v,t}^{(\ell)} = \frac{1}{S_A} \sum_{s=1}^{S_A} m_{v,t}^{(\ell,s)}. \tag{A.3}$$

Loss Functions. For the masked autoencoder (MAE) objective, masked position sizes are predicted as $\hat{w}_{ia,t} = f_{\mathrm{AE}}(e_{i,t}, e_{a,t})$. The autoencoder loss is $\mathcal{L}_{\mathrm{AE}} = \sum_{(i,a) \in \mathcal{V}_{\mathrm{masked},t}} (g(w_{ia,t}) - g(\hat{w}_{ia,t}))^2$, where $g(\cdot) = \mathrm{sgn}(\cdot) \log(|\cdot|)$. The supervised trade prediction loss combines binary cross-entropy for the extensive margin and mean squared error for the intensive margin:

$$\mathcal{L}_{\mathrm{TP}} = \sum_{(i,a) \in \mathcal{V}_t} \mathrm{BCE}(\hat{c}_{ia,t+1}, \mathbf{1}[y_{ia,t+1} \neq 0]) + \sum_{\substack{(i,a) \in \mathcal{V}_t \\ y_{ia,t+1} \neq 0}} (y_{ia,t+1} - \hat{m}_{ia,t+1})^2, \tag{A.4}$$

where $\mathrm{BCE}(\hat{c}, y) = -[y \log \sigma(\hat{c}) + (1-y)\log(1-\sigma(\hat{c}))]$. The overall training procedure minimizes these losses sequentially:

$$\text{Phase 1: } \min_{\Theta_{\text{Backbone}}, \Theta_{\text{AE}}} \mathcal{L}_{\text{AE}}, \qquad \text{Phase 2: } \min_{\Theta_{\text{Backbone}}, \Theta_{\text{TP}}} \mathcal{L}_{\text{TP}}, \tag{A.5}$$

where Θ_{Backbone}, Θ_{AE}, and Θ_{TP} denote the learnable parameter vectors for the GNN backbone, masked autoencoder head, and trade prediction head, respectively.

Model Parameters. The trainable components include the feature map ϕ, the pre-embedding functions for categorical characteristics, the message feed-forward layers $M^{(\ell)}$, the attention mechanism projection matrices W_{qs} and W_{ks}, the node update function $U^{(\ell)}$, the embeddings projection layer ρ, and the task-specific prediction heads f_{AE} and f_{TP}. We collect the set of parameters in all these learnable components in the vector Θ.

C Benchmark Model Details

This appendix describes the benchmark models used in the trade prediction comparison of Table 4. All models predict the same target: the trade outcome ($y_{ia,t+1}$) for each investor-asset pair, defined as $\log(q_{ia,t+1}/q_{ia,t})$. All models use a hurdle-style (classification plus regression) architecture and condition on the aggregate state ζ_{t+1} where applicable, and are evaluated on identical held-out test quarters using the same train-validation-test split.

Persistence. The simplest time-series benchmark: the predicted $y_{ia,t+1}$ at quarter t equals the realized $y_{ia,t+1}$ at quarter $t-1$ for the same investor-asset pair, $\hat{y}_{ia,t+1} = y_{ia,t}$. For edges that do not appear in the previous quarter (new positions or re-entries), the forecast is zero. This model tests whether $y_{ia,t+1}$ indicators exhibit positive autocorrelation—i.e., whether investors who bought last quarter tend to buy again this quarter. It uses no graph structure and is not inductive.

Ridge regression. A linear model with L2 regularization ($\alpha = 10$) fit on a per-edge feature vector comprising investor characteristics , asset characteristics, the FSI financial stress index, and the L2 norms of the investor and asset feature vectors. Features are standardized before estimation. This model serves as the pure cross-sectional baseline; it uses no network structure.

Gradient boosting (XGBoost). XGBoost with 500 histogram-based boosted regression trees, using the same augmented feature set as network-augmented ridge. Hyperparameters: max depth 6, learning rate 0.05, subsample rate 0.8. Training is subsampled to 2 million edges. Comparing XGBoost to network-augmented ridge isolates the contribution of nonlinear feature interactions from the GNN's ability to propagate information through the graph.

Two-tower recommender system. A factorized deep learning model inspired by industrial recommendation systems. Each investor and asset is embedded via a separate MLP "tower" that maps its numeric and categorical features to a 64-dimensional representation. Each tower consists of two fully connected layers (hidden dimension 128) with ReLU activations and dropout. The per-edge prediction is produced by an interaction head that takes the concatenation of the two tower outputs and the current log holding value and maps it through a two-layer MLP to a scalar prediction, using a hurdle-style loss (binary cross-entropy for the trade-or-not decision plus MSE on nonzero targets). The model is trained using AdamW (learning rate 10^{-3}, weight decay 0.01) with learning rate reduction on plateau and early stopping (patience 5). This model is inductive—it generalizes to unseen investors and assets through its feature-based towers—but it does not perform message passing or neighbor aggregation.

D Architecture Ablations

Table A.I reports ablation experiments that evaluate the contribution of individual architectural components to $y_{ia,t+1}$ prediction accuracy. Each row modifies a single design choice relative to the baseline three-layer graph transformer with attention-based aggregation, skip connections, hidden dimension $h = 256$, and the hurdle prediction head. The WF R^2 column reports walk-forward out-of-sample R^2 from expanding-window retraining, confirming that the ablation rankings are broadly preserved in the temporal out-of-sample setting.

Table A.I: **Architecture ablation study**

Variant	AUC	RegCorr	R^2 (%)	WF R^2 (%)
Attention-augmented GNN (baseline)	**0.860**	**0.330**	**11.0**	**6.6**
No attention	0.820	0.276	7.5	3.2
No skip connections	0.791	0.228	5.2	1.8
Single GNN layer	0.821	0.287	8.0	2.5
No FSI conditioning	0.820	0.281	4.7	4.3
Shuffled edges (topology destroyed)	0.780	0.159	2.2	2.3

Notes: Ablation study for the graph transformer architecture trained on supervised trade prediction. *Architecture ablations*: "No attention" replaces attention heads with SAGEConv (mean aggregation). "No skip connections" removes residual connections between GNN layers. "Single GNN layers" performs only one layer of message passing. "No FSI conditioning" removes the ζ_{t+1} scalar input from the trade prediction head. "Shuffled edges" randomly permutes asset-side edge indices to destroy network topology while preserving node features and degree distributions. AUC is for the binary classification head (trade vs. no trade). RegCorr and R^2 are computed on the nonzero-trade subset. "WF R^2" is from expanding-window walk-forward retraining; each ablation variant is retrained from scratch in each window.

E Historical Expectations and Incremental Targeting

The main text normalizes the benchmark to "no intervention" ($\tau = 0$) when defining the cross-sectional liquidation sufficient statistic $L(q)$. A common critique is that historically the private sector expected some form of intervention, so the observed behavior does not correspond to a $\tau = 0$ world. This appendix shows that the core ex-post targeting results extend verbatim once the benchmark is redefined as *no incremental intervention relative to an incumbent baseline policy regime.*

Baseline regime and deviations. Fix a baseline (historically expected) policy regime, summarized in the Middle period by a baseline wedge vector

$$\tau^\pi \in \mathbb{R}^{NI},$$

which is common knowledge when private agents choose liquidations. The regulator may additionally choose a *discretionary deviation* (or incremental wedge)

$$\tilde{\tau} \in \mathbb{R}^{NI}, \qquad \text{so that} \qquad \tau = \tau^\pi + \tilde{\tau}.$$

The regulator incurs a quadratic cost in deviations,

$$\delta(\tilde{\tau}) \;=\; \frac{1}{2}\,\tilde{\tau}^\top \Delta \tilde{\tau}, \tag{A.6}$$

for a symmetric matrix $\Delta \succeq 0$ (as in the main text).

Information. Maintain the information structure of the main text: in the Middle period, private agents observe the true structural state Φ relevant for their liquidation decisions, while the regulator observes a model-dependent signal s and forms posterior beliefs $\mathbb{E}[\cdot \mid s, M]$. This preserves the main text's "no informational externality" channel: conditional on Φ, private reaction functions do not depend on (s, M).

Baseline-regime liquidation pressure. Let $\ell_i \in \mathbb{R}^N$ denote intermediary i's liquidation vector, and $L = \sum_i \ell_i \in \mathbb{R}^N$ the total liquidation vector. As in the main text, stack individual liquidations as $\ell = (\ell_1^\top, \ldots, \ell_I^\top)^\top \in \mathbb{R}^{NI}$ and define $q = (q_1^\top, \ldots, q_I^\top)^\top$.

Definition 1 (Baseline-regime liquidation sufficient statistic)**.** *Given positions q, define* baseline-regime (no-deviation) liquidations *as the equilibrium outcomes under wedges $\tau = \tau^\pi$ (i.e., $\tilde{\tau} = 0$):*

$$\ell_i^\pi(q) \;\equiv\; \ell_i(q, \tau^\pi), \qquad L^\pi(q) \;\equiv\; \sum_{i=1}^{I} \ell_i^\pi(q).$$

Middle equilibrium under a baseline regime. The main text shows that, under the maintained linear-quadratic structure, equilibrium liquidations are affine in (q, τ) and prices are affine in L. We restate this mapping in deviation form for later use.

Lemma 2 (Equilibrium mapping in deviations around τ^π)**.** *Suppose the Middle-period equilibrium mapping in the main text can be written as*

$$\ell \;=\; \bar{\ell} + \Lambda_q q - \Lambda_\tau \tau, \qquad \gamma \;=\; \bar{\gamma} - \Gamma L, \qquad L = \sum_{i=1}^{I} \ell_i, \tag{A.7}$$

for matrices Λ_q, Λ_τ and symmetric Γ. Let $\tau = \tau^\pi + \tilde{\tau}$. Then equilibrium liquidations and total liquidations admit the deviation decomposition

$$\ell = \ell^\pi(q) - \Lambda_\tau \tilde{\tau}, \tag{A.8}$$

$$L = L^\pi(q) - \Big(\sum_{i=1}^{I} \Lambda_{\tau i}\Big)\tilde{\tau}, \tag{A.9}$$

where $\ell^\pi(q) \equiv \bar{\ell} + \Lambda_q q - \Lambda_\tau \tau^\pi$ and $L^\pi(q) \equiv \sum_i \ell_i^\pi(q)$.

Proof. Substitute $\tau = \tau^\pi + \tilde{\tau}$ into (A.7):

$$\ell = \bar{\ell} + \Lambda_q q - \Lambda_\tau(\tau^\pi + \tilde{\tau}) = (\bar{\ell} + \Lambda_q q - \Lambda_\tau \tau^\pi) - \Lambda_\tau \tilde{\tau} = \ell^\pi(q) - \Lambda_\tau \tilde{\tau},$$

which yields (A.8). Summing blocks across intermediaries gives (A.9), with the same block-aggregation convention as in the main text. □

Optimal incremental wedges. We now re-solve the regulator's ex-post targeting problem when the instrument is the *incremental* wedge $\tilde{\tau}$ rather than the level wedge τ.

Proposition 6 (Optimal discretionary wedges around a baseline regime)**.** *Maintain the main text's assumptions (including symmetry of Γ and the quadratic deviation cost (A.6)). Fix positions q. Then conditional on (s, M) the optimal incremental wedges $\tilde{\tau}^*(s, M)$ satisfy*

$$\tilde{\tau}^*(s, M) = \mathbb{E}[\Xi \mid s, M]^{-1}\, \mathbb{E}\left[\Big(\sum_{i=1}^{I} \Lambda_{\tau i}\Big)^{\top} \Gamma\, L^\pi(q) \,\middle|\, s, M\right], \tag{A.10}$$

where

$$\Xi = \Lambda_\tau^\top + \Big(\sum_{i=1}^{I} \Lambda_{\tau i}\Big)^{\top} \Gamma \Big(\sum_{i=1}^{I} \Lambda_{\tau i}\Big) + \Delta. \tag{A.11}$$

Proof. The proof mirrors the main text's derivation, with the only difference being the normalization of the policy benchmark.

Step 1: deviation representation. By Lemma 2,

$$L = L^\pi(q) - B\tilde{\tau}, \qquad \gamma = \bar{\gamma} - \Gamma L, \qquad B \equiv \sum_{i=1}^{I} \Lambda_{\tau i}.$$

Step 2: quadratic objective in $\tilde{\tau}$. Under the maintained LQ structure in the main text, after substituting the equilibrium mapping into the regulator's ex-post objective and using the envelope theorem for intermediaries' choices, the regulator's conditional objective can be written (up to terms constant in $\tilde{\tau}$) as a quadratic function

$$W(\tilde{\tau}; s, M) = \mathbb{E}\left[\tilde{\tau}^\top B^\top \Gamma L^\pi(q) - \frac{1}{2}\tilde{\tau}^\top \left(\Lambda_\tau^\top + B^\top \Gamma B\right)\tilde{\tau} \;\middle|\; s, M\right] - \frac{1}{2}\tilde{\tau}^\top \Delta \tilde{\tau}. \qquad \text{(A.12)}$$

The $B^\top \Gamma B$ term arises from the induced change in prices through $L = L^\pi(q) - B\tilde{\tau}$, and $\Lambda_\tau^\top$ collects the direct marginal-cost terms from intermediaries' liquidation responses, exactly as in the main text. The baseline wedge τ^π only affects the intercept $L^\pi(q)$ and hence enters the linear term in (A.12).

Step 3: first-order condition. Differentiating (A.12) with respect to $\tilde{\tau}$ yields the conditional FOC

$$0 = \mathbb{E}\Big[B^\top \Gamma L^\pi(q) \mid s, M\Big] - \mathbb{E}\Big[(\Lambda_\tau^\top + B^\top \Gamma B)\tilde{\tau} \mid s, M\Big] - \Delta\tilde{\tau}.$$

Rearranging,

$$\mathbb{E}[\Xi \mid s, M]\tilde{\tau} = \mathbb{E}[B^\top \Gamma L^\pi(q) \mid s, M],$$

with Ξ given by (A.11). Solving for $\tilde{\tau}$ yields (A.10). □

Definition 2 (Predictive–causal independence)**.** *We say predictive–causal independence holds if the policy transmission objects $\{\Lambda_{\tau i}\}_{i=1}^{I}$ (equivalently $B = \sum_i \Lambda_{\tau i}$) are independent of the objects governing baseline-regime liquidation pressure $L^\pi(q)$.*

Corollary 3 (Baseline-regime analogue of equation (9))**.** *Under predictive–causal independence (Definition 2), the optimal incremental wedges factor as*

$$\tilde{\tau}^*(s, M) = \underbrace{\mathbb{E}[\Xi \mid s, M]^{-1}\, \mathbb{E}\left[\left(\sum_{i=1}^{I} \Lambda_{\tau i}\right)^\top \Gamma \;\middle|\; s, M\right]}_{\textit{Transmission / causal term}} \underbrace{\mathbb{E}[L^\pi(q) \mid s, M]}_{\textit{Predictive sufficient statistic under } \pi}. \qquad \text{(A.13)}$$

Proof. From Proposition 6,

$$\tilde{\tau}^* = \mathbb{E}[\Xi \mid s, M]^{-1}\mathbb{E}\Big[B^\top \Gamma L^\pi(q) \mid s, M\Big].$$

Under predictive–causal independence, conditional on (s, M) the random matrix $B^\top \Gamma$ is independent of the random vector $L^\pi(q)$, so $\mathbb{E}[B^\top \Gamma L^\pi(q) \mid s, M] = \mathbb{E}[B^\top \Gamma \mid s, M]\mathbb{E}[L^\pi(q) \mid s, M]$. Substituting yields (A.13). $\square$

Remark 1 (How this addresses the "bailout expectations" critique)**.** *The sufficient statistic for* incremental *ex-post targeting is $L^\pi(q)$ (or its forecast), not liquidation pressure in a counterfactual world with $\tau \equiv 0$ forever. Empirically, data generated under the historical regime π identify $L^\pi(q)$ and the relevant transmission objects, which are precisely what enter* (A.13)*.*

Value of prediction and optimal model choice under a baseline regime. This subsection extends the main text's welfare and model-selection results by replacing $L(q)$ with $L^\pi(q)$ and τ with $\tilde{\tau}$.

Define the baseline-regime forecast

$$\widehat{L}^\pi(q) \;\equiv\; \mathbb{E}[L^\pi(q) \mid s, M]\,.$$

Proposition 7 (Expected welfare depends on prediction only through $\mathrm{cov}_0(\widehat{L}^\pi(q))$)**.** *Maintain predictive–causal independence and restrict attention to predictive models (in the sense of the main text). Then ex-ante expected welfare admits the decomposition*

$$V^\pi(q, M) = V^\pi_{\textit{no-dev}}(q) + \frac{1}{2}\,\mathbb{E}_0\Big[\widehat{L}^\pi(q)^\top \Theta_0\, \widehat{L}^\pi(q)\Big]\,, \tag{A.14}$$

for a positive semidefinite weight matrix Θ_0 (defined below), and where $V^\pi_{\textit{no-dev}}(q)$ is welfare under $\tilde{\tau} = 0$ (i.e., under baseline π only). Equivalently,

$$V^\pi(q, M) = \widetilde{V}^\pi(q) + \frac{1}{2}\,\mathrm{tr}\Big(\Theta_0\, \mathrm{cov}_0(\widehat{L}^\pi(q))\Big)\,, \tag{A.15}$$

where $\widetilde{V}^\pi(q)$ does not depend on M.

Proof. We provide a self-contained quadratic-form argument (the same algebra as in the main text, with baseline π shifting intercepts).

Step 1: conditional problem. Under the LQ structure, Proposition 6 implies

$$\tilde{\tau}^*(s, M) = \Upsilon(s, M)\, \widehat{L}^\pi(q), \qquad \Upsilon(s, M) \equiv \mathbb{E}[\Xi \mid s, M]^{-1}\, \mathbb{E}[B^\top \Gamma \mid s, M], \quad B = \sum_i \Lambda_{\tau i}.$$

Substituting the equilibrium mapping into the regulator objective yields (up to constants) a conditional quadratic welfare improvement of the form

$$\Delta W(s, M) = \frac{1}{2}\, \widehat{L}^\pi(q)^\top \Theta(s, M)\, \widehat{L}^\pi(q), \qquad \Theta(s, M) \equiv \Upsilon(s, M)^\top \Psi(s, M)\, \Upsilon(s, M),$$

where $\Psi(s, M)$ is the conditional "marginal-cost-of-tilting" matrix (the same object as in the main text: it is the Hessian in $\tilde{\tau}$ of the negative welfare term). Thus conditional welfare equals

$$V^{\pi}(q, M, s) = V^{\pi}_{\text{no-dev}}(q, s) + \frac{1}{2}\,\widehat{L}^{\pi}(q)^{\top}\Theta(s, M)\,\widehat{L}^{\pi}(q).$$

Step 2: take ex-ante expectation and use the predictive restriction. Taking $\mathbb{E}_0[\cdot \mid M]$ yields

$$V^{\pi}(q, M) = V^{\pi}_{\text{no-dev}}(q) + \frac{1}{2}\,\mathbb{E}_0\Big[\widehat{L}^{\pi}(q)^{\top}\Theta(s, M)\,\widehat{L}^{\pi}(q)\Big].$$

Under the restriction to predictive models, $\Theta(s, M)$ is invariant to the forecast quality (i.e., it depends only on transmission/cost primitives), and under predictive–causal independence we may replace $\Theta(s, M)$ by its ex-ante mean $\Theta_0 \equiv \mathbb{E}_0[\Theta(s, M) \mid M]$ without affecting comparative statics in forecast dispersion. This gives (A.14).

Step 3: trace form. Finally,

$$\mathbb{E}_0\Big[\widehat{L}^{\pi\top}\Theta_0\widehat{L}^{\pi}\Big] = \mathbb{E}_0[\widehat{L}^{\pi}]^{\top}\Theta_0\,\mathbb{E}_0[\widehat{L}^{\pi}] + \operatorname{tr}\Big(\Theta_0\,\operatorname{cov}_0(\widehat{L}^{\pi})\Big).$$

By iterated expectations, $\mathbb{E}_0[\widehat{L}^{\pi}] = \mathbb{E}_0[L^{\pi}]$, which is model-invariant across predictive models. Absorb the mean term into $\widetilde{V}^{\pi}(q)$ to obtain (A.15). □

Proposition 8 (Optimal predictive model choice under baseline π)**.** *Under the assumptions of Proposition 7, when restricting attention to predictive models the regulator's optimal model choice solves the matrix first-order condition*

$$\frac{\partial \mathcal{C}(\Sigma^{\pi}_{\widehat{L},0}, q)}{\partial \Sigma^{\pi}_{\widehat{L},0}} + \left(\frac{\partial \mathcal{C}(\Sigma^{\pi}_{\widehat{L},0}, q)}{\partial \Sigma^{\pi}_{\widehat{L},0}}\right)^{\top} = \Theta_0, \tag{A.16}$$

where $\Sigma^{\pi}_{\widehat{L},0} \equiv \operatorname{cov}_0(\widehat{L}^{\pi}(q))$ *and* $\mathcal{C}(\cdot, q)$ *is the (possibly model-dependent) resource cost of achieving forecast dispersion* $\Sigma^{\pi}_{\widehat{L},0}$.

Proof. By (A.15), across predictive models welfare depends on M only through $\Sigma^{\pi}_{\widehat{L},0}$, with objective

$$\max_{\Sigma^{\pi}_{\widehat{L},0} = \Sigma^{\pi\top}_{\widehat{L},0}} \frac{1}{2}\operatorname{tr}\Big(\Theta_0\,\Sigma^{\pi}_{\widehat{L},0}\Big) - \mathcal{C}(\Sigma^{\pi}_{\widehat{L},0}, q).$$

Taking the Fréchet derivative with respect to the symmetric matrix $\Sigma^{\pi}_{\widehat{L},0}$ yields (A.16). □

Corollary 4 (Weighted R^2 characterization under baseline π)**.** *Let* $\langle x, y\rangle_{\Theta_0} \equiv x^{\top}\Theta_0 y$ *and define the* Θ_0*-weighted variance* $\operatorname{Var}_{\Theta_0}(X) \equiv \mathbb{E}_0[\langle X - \mathbb{E}_0[X], X - \mathbb{E}_0[X]\rangle_{\Theta_0}]$. *Then, among predictive models, the welfare gain from forecasting is*

$$\Delta V^{\pi}(M) = \Delta V^{\pi}_{\max} \cdot \rho^2_{\Theta_0}(M),$$

where $\rho_{\Theta_0}(M)$ is the Θ_0-weighted correlation between $L^\pi(q)$ and its forecast $\widehat{L}^\pi(q)$, and $\Delta V^\pi_{\max}$ is the gain under a perfect forecast $\widehat{L}^\pi(q) = L^\pi(q)$.

Proof. By (A.15),

$$\Delta V^\pi(M) = \frac{1}{2}\operatorname{tr}\Big(\Theta_0 \operatorname{cov}_0(\widehat{L}^\pi)\Big) = \frac{1}{2}\operatorname{Var}_{\Theta_0}(\widehat{L}^\pi).$$

Under a perfect forecast, $\Delta V^\pi_{\max} = \dfrac{1}{2}\operatorname{Var}_{\Theta_0}(L^\pi)$. The standard identity $\operatorname{Cov}_{\Theta_0}(L^\pi, \widehat{L}^\pi) = \operatorname{Var}_{\Theta_0}(\widehat{L}^\pi)$ (which follows from $\widehat{L}^\pi = \mathbb{E}[L^\pi \mid s, M]$) implies $\rho^2_{\Theta_0}(M) = \operatorname{Var}_{\Theta_0}(\widehat{L}^\pi)/\operatorname{Var}_{\Theta_0}(L^\pi)$, which yields the result. □

F A Generalized Targeting Statistic

This appendix relaxes the quadratic absorption technology used to obtain the linear price map $\gamma = \bar{\gamma} - \Gamma L$. With a general convex absorption cost, the equilibrium price map is nonlinear, and the optimal targeting rule is generally implicit. We provide (i) the exact pricing relation and (ii) a local (second-order) analogue of the main text's equation (9) that identifies a generalized sufficient statistic.

Assumption 2 (General convex absorption cost)**.** *Arbitrageurs (or the marginal absorbing sector) face a convex, twice continuously differentiable absorption cost $C : \mathbb{R}^N \to \mathbb{R}$ with $\nabla^2 C(L) \succeq 0$. Competitive absorption implies the pricing relation*

$$\gamma \;=\; \bar{\gamma} - \nabla C(L), \tag{A.17}$$

so the (local) price-impact matrix is $\Gamma(L) \equiv \nabla^2 C(L)$.

Remark 2. *When $C(L) = \dfrac{1}{2}L^\top \Gamma L$, (A.17) reduces to the benchmark $\gamma = \bar{\gamma} - \Gamma L$.*

With a nonlinear price map, closed forms typically require approximation. Fix a baseline regime π and positions q. Let $L^\pi(q)$ denote baseline-regime total liquidations (Definition 1) and define the local curvature

$$\Gamma^\pi(q) \;\equiv\; \Gamma(L^\pi(q)) = \nabla^2 C(L^\pi(q)).$$

Proposition 9 (Local analogue of equation (9) under convex absorption costs)**.** *Maintain the main text's LQ structure for intermediaries, the baseline-regime setup in Appendix E, and Assumption 2. Consider small deviations $\tilde{\tau}$ around $\tilde{\tau} = 0$ (i.e. around $\tau = \tau^\pi$). Let*

$$B^\pi(q) \;\equiv\; -\left.\frac{\partial L}{\partial \tilde{\tau}}\right|_{\tilde{\tau}=0} \quad \in \mathbb{R}^{N \times NI}$$

denote the (equilibrium) policy impact matrix at the baseline. Then a second-order approximation *to the regulator's conditional problem yields the local optimal deviation rule*

$$\tilde{\tau}^{*,loc}(s,M) = \mathbb{E}[\Xi_C^\pi(q) \mid s,M]^{-1} \, \mathbb{E}\Big[B^\pi(q)^\top \, \Gamma^\pi(q) \, L^\pi(q) \, \Big| \, s,M\Big], \tag{A.18}$$

where

$$\Xi_C^\pi(q) \;\equiv\; \Lambda_\tau^\top + B^\pi(q)^\top \, \Gamma^\pi(q) \, B^\pi(q) + \Delta. \tag{A.19}$$

In the quadratic benchmark, $B^\pi(q) = \sum_i \Lambda_{\tau i}$ and $\Gamma^\pi(q) = \Gamma$, so (A.18) reduces to the baseline-regime analogue of equation (9).

Proof. By Assumption 2, the price map is $\gamma(L) = \bar{\gamma} - \nabla C(L)$, so for small changes ΔL around $L^\pi(q)$,

$$\Delta\gamma = \gamma(L^\pi + \Delta L) - \gamma(L^\pi) = -\nabla^2 C(L^\pi)\, \Delta L + o(\|\Delta L\|) = -\Gamma^\pi(q)\, \Delta L + o(\|\Delta L\|).$$

By definition of $B^\pi(q)$, the equilibrium change in total liquidations induced by a small deviation $\tilde{\tau}$ satisfies $\Delta L = -B^\pi(q)\tilde{\tau} + o(\|\tilde{\tau}\|)$. Therefore,

$$\Delta\gamma = \Gamma^\pi(q)\, B^\pi(q)\tilde{\tau} + o(\|\tilde{\tau}\|).$$

As in the main text, the welfare-relevant marginal benefit from raising prices is the baseline quantity vector times the induced price change, giving the (local) linear term $\tilde{\tau}^\top B^{\pi\top}\Gamma^\pi L^\pi$. The (local) quadratic term in $\tilde{\tau}$ collects (i) the direct marginal costs from intermediaries' liquidation responses (captured by $\Lambda_\tau^\top$ under the LQ structure), (ii) the general-equilibrium price-feedback term $B^{\pi\top}\Gamma^\pi B^\pi$, and (iii) the deviation cost Δ. Hence the regulator's second-order approximation is (up to constants)

$$W^{\text{loc}}(\tilde{\tau}; s, M) = \mathbb{E}\left[\tilde{\tau}^\top B^{\pi\top}\Gamma^\pi L^\pi - \frac{1}{2}\tilde{\tau}^\top(\Lambda_\tau^\top + B^{\pi\top}\Gamma^\pi B^\pi)\tilde{\tau} \;\middle|\; s, M\right] - \frac{1}{2}\tilde{\tau}^\top\Delta\tilde{\tau}.$$

The conditional first-order condition is therefore

$$0 = \mathbb{E}\Big[B^{\pi\top}\Gamma^\pi L^\pi \mid s, M\Big] - \mathbb{E}\Big[(\Lambda_\tau^\top + B^{\pi\top}\Gamma^\pi B^\pi)\tilde{\tau} \mid s, M\Big] - \Delta\tilde{\tau},$$

which rearranges to (A.18) with $\Xi_C^\pi(q)$ as in (A.19). $\square$

A generalized (price-relevant) targeting statistic. A key takeaway from Proposition 9 is that, under convex absorption costs, the benchmark liquidation statistic $L^\pi(q)$ is no longer sufficient by itself for price-based targeting: the relevant object is the *curvature-weighted liquidation pressure.*

Definition 3 (Generalized targeting statistic under convex absorption)**.** *Define the generalized* *baseline-regime targeting statistic*

$$\widetilde{L}^{\pi}(q) \;\equiv\; \Gamma^{\pi}(q)\, L^{\pi}(q) = \nabla^2 C(L^{\pi}(q))\, L^{\pi}(q). \tag{A.20}$$

Corollary 5 (Local factorization (equation (9)-style) using $\widetilde{L}^{\pi}(q)$)**.** *Suppose (local) predictive–causal independence holds in the sense that $B^{\pi}(q)$ is independent of $\widetilde{L}^{\pi}(q)$ conditional on (s, M). Then the local optimal rule (A.18) factors as*

$$\tilde{\tau}^{*,loc}(s, M) = \mathbb{E}[\Xi^{\pi}_{C}(q) \mid s, M]^{-1}\, \mathbb{E}[B^{\pi}(q)^{\top} \mid s, M]\, \mathbb{E}[\widetilde{L}^{\pi}(q) \mid s, M].$$

Proof. Immediate from (A.18) and the conditional independence assumption. □

G A Simple Quantitative Welfare Calibration

We provide a rough back-of-the-envelope calibration of the welfare implications of the model's predictions. This exercise rests on several simplifying approximations and is intended to give a sense of magnitudes rather than precise welfare estimates. Corollary 2 shows that the welfare gain from a predictive model is

$$\Delta V(M) = \Delta V_{\max} \cdot \rho^2_{\Theta_0}(M), \tag{A.21}$$

where $\Delta V_{\max} = \frac{1}{2}\mathrm{tr}(\Theta_0 \,\mathrm{cov}(L))$ is the welfare gain from a perfect forecast and $\rho^2_{\Theta_0}(M)$ is the model's Θ_0-weighted R-squared. We calibrate each component in turn.

We approximate Θ_0 using Harberger deadweight losses from fire-sale price distortions. The welfare weight for asset a is calibrated to be:

$$\theta_a = \frac{v_a}{\mathrm{ADV}_a^{2\beta}}, \tag{A.22}$$

where $v_a = \sum_i w_{ia}$ is total held value, ADV_a is average daily dollar volume, and $\beta = 0.25$ is the permanent price impact exponent.[1] This parameterization isolates the price-impact component of Θ_0. In the full model (Proposition 2), Θ_0 also reflects the regulatory cost Δ and the holding cost channel through H^{ℓ}; to the extent that these additional channels are quantitatively important, our calibration understates the welfare weight on assets with high adjustment costs. Using this calibration, and taking the out-of-sample predictive performance of the GNN model on the cross-sectional trade prediction task as a proxy for the predictive performance on the theoretical targeting statistics, we obtain a Θ_0-weighted R-squared value of $\rho^2_{\Theta_0} = 10.8\%$.

The most challenging object to calibrate is $\Delta V_{\max}$. We anchor it from calibrated macro-finance models: Bianchi (2011) estimates the welfare cost of overborrowing externalities at 0.24–5.1% of consumption, and Elenev et al. (2021) calibrate welfare gains from optimal bank capital regulation

[1] Kyle (1985) derives $\lambda \propto 1/\sqrt{V}$ ($\beta = 0.5$) for temporary impact. The permanent component decays more slowly: $\beta \approx 0.2$–0.4 in the literature (Bouchaud et al., 2018).

Table A.II: **Calibrated welfare gains from the predictive model**

	Fire-sale externality $\Delta V_{\max}$ (% of consumption)					
	0.24%		0.42%		2.0%	
	\$B	% of C	\$B	% of C	\$B	% of C
Graph transformer ($\rho^2_{\Theta_0} = 10.8\%$)	\$3.0B	0.026%	\$5.2B	0.045%	\$24.9B	0.216%

Notes: Back-of-the-envelope welfare calibration using Corollary 2: $\Delta V(M) = \Delta V_{\max} \cdot \rho^2_{\Theta_0}(M)$. The welfare weight for asset a is calibrated to $\theta_a = v_a/\text{ADV}_a^{2\beta}$ with $\beta = 0.25$. $\Delta V_{\max}$ is anchored from calibrated macro-finance models: 0.24% and 2.0% of consumption from Bianchi (2011), 0.42% from Elenev et al. (2021). Consumption equivalents use mean US PCE.

at 0.42% of consumption.[2] An important caveat is that these calibrations measure the total welfare cost of fire-sale or overborrowing externalities in the absence of optimal regulation. $\Delta V_{\max}$ is a related but distinct object: the welfare gain from perfectly targeting an ex-post intervention given the regulator's available instruments. This gain is bounded above by the total externality cost but may be smaller if the regulator's instruments are incomplete (Δ large) or if causal leverage on liquidation prices is limited.

Applying $\rho^2_{\Theta_0} = 10.8\%$ to these literature anchors yields the estimates in Table A.II. Under the central estimate for externality size (0.42% from Elenev et al. 2021), the model generates welfare gains of approximately 0.045% of consumption (\$5.2B per quarter). Under the upper-bound estimate (2.0% from Bianchi 2011), the gain rises to 0.22% of consumption (\$24.9B per quarter).

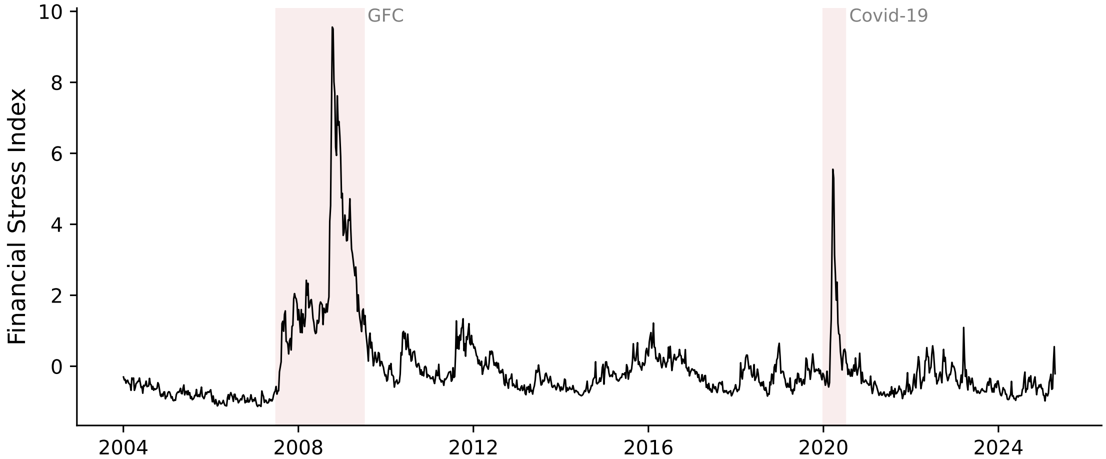
Table A.III: **Informational content of learned embeddings**

Measure	Value
All obs. $\to$ inv. emb. (R^2)	0.535
All obs. $\to$ asset emb. (R^2)	0.495
Asset emb. sim. $\leftrightarrow$ co-holding (ρ, all)	0.267
Asset emb. sim. $\leftrightarrow$ co-holding (ρ, same class)	0.269
Asset emb. sim. $\leftrightarrow$ co-holding (ρ, diff. class)	0.234

Notes: The table reports the variance-weighted R^2 of all observable characteristics jointly predicting each embedding dimension, and Pearson correlations between pairwise asset embedding cosine similarity and log co-holding (number of shared investors) for asset pairs with at least one shared holder.

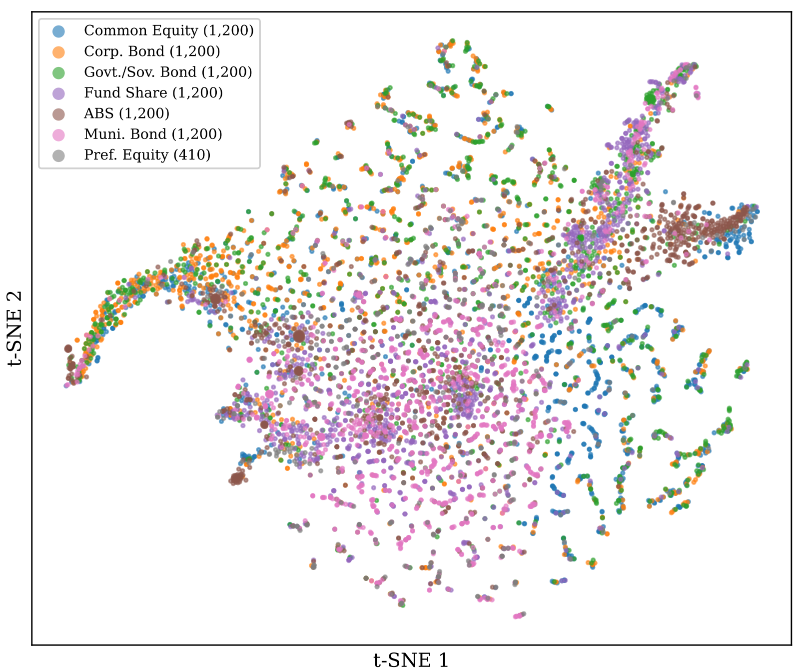
[2] We use mean US personal consumption expenditures as the consumption base, following Bianchi (2011) and Elenev et al. (2021).

Figure A.I: **St. Louis Fed Financial Stress Index**



Notes: Weekly observations; shaded regions indicate the Global Financial Crisis (2007–2009) and the Covid-19 crisis (2020). The index is centered at zero, with positive values indicating above-average financial stress.

Figure A.II: **t-SNE visualization of learned asset embeddings**



Notes: Each point represents an asset's 128-dimensional GNN embedding, projected to two dimensions via t-SNE (perplexity = 50, 2,000 iterations). To reveal spatial structure, we first remove the dominant principal component (which captures a global scale factor due to layer normalization) and then reduce to 50 dimensions via PCA before applying t-SNE. Colors indicate asset class. The embeddings are extracted from the trained model applied to the 2020Q1 holdings cross-section.