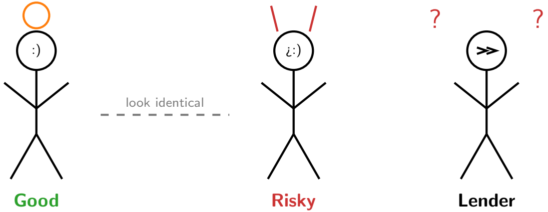
P2P Lending & Robo-Advisors

Lesson 03

Digital Finance

Loans: One Rate Fits All



When you can't tell good from bad, everyone pays the average price.

Outline

Learning Objectives

By the end of this lesson, you will be able to:

1. Explain **adverse selection**, **moral hazard**, and the **principal-agent problem** in lending markets
2. Describe how P2P platforms use technology to mitigate information asymmetry
3. Explain risk-return basics and how robo-advisors apply portfolio diversification
4. Analyze how data-driven approaches transform lending and advisory
5. Compare technology-enabled financial services with traditional counterparts

Connection: This lesson applies Lesson 01's information asymmetry concepts to lending and investment.

These five objectives frame the conceptual progression from information problems to technology solutions.

Why Do the Riskiest Borrowers Want Loans the Most?

Imagine you're a lender looking at two loan applications. The riskier borrower is MORE eager to borrow — and you can't tell the difference.

Adverse selection occurs *before* a transaction when one party has more information than the other.

In lending markets:

- Borrowers know their true creditworthiness better than lenders
- The riskiest borrowers are often the most eager to borrow (highest willingness to pay high interest)
- George Akerlof's "**market for lemons**" analogy: bad borrowers drive out good borrowers
- Without information, lenders charge an average interest rate that is too high for low-risk borrowers (who exit the market) and too low for high-risk borrowers (who stay)

Traditional bank solutions:

- **Relationship lending:** Long-term interactions reveal borrower quality
- **Collateral:** Tangible assets reduce lender risk
- **Credit bureaus:** Shared information about past behavior

Adverse selection explains why credit markets don't work like simple supply-and-demand.

What Happens After the Loan Is Signed?

Moral hazard occurs *after* a transaction when one party may change behavior because risk is borne by another.

In lending:

- A borrower may take more risks with borrowed money than with their own
- After receiving a loan, the borrower's incentive to repay may weaken
- Example: A business loan used for a speculative investment instead of the stated purpose

Principal-agent problem:

- **Principal:** The party delegating authority (lender, investor, client)
- **Agent:** The party acting on behalf of the principal (borrower, fund manager, financial advisor)
- **Problem:** The agent may not act in the principal's best interest due to misaligned incentives or hidden actions

Solutions: Monitoring, incentive alignment (performance fees, skin in the game), disclosure requirements.

Moral hazard and principal-agent problems recur in Lessons 04, 06, and 07.

Can a Platform Replace a Bank – and Who Bears the Risk?

Traditional financial intermediation:

Saver $\rightarrow$ **Bank** $\rightarrow$ Borrower

Peer-to-peer disintermediation:

Saver $\rightarrow$ **Platform** $\rightarrow$ Borrower

Why disintermediation can create value:

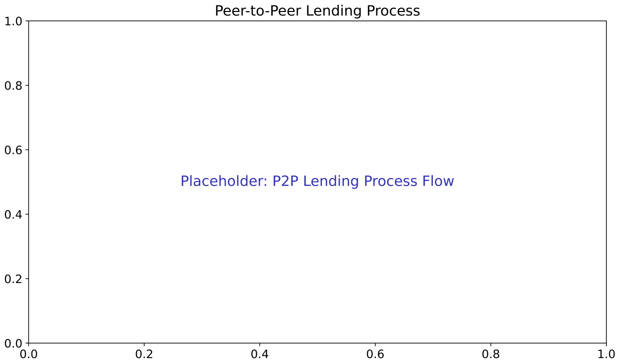
- Banks incur costs: physical branches, regulatory compliance, deposit insurance
- If a technology platform can solve information asymmetry problems *more cheaply* than traditional banks, it can offer better rates to both sides
- Lower overhead $\rightarrow$ higher returns for savers, lower rates for borrowers

Critical question: Who bears the risk?

- Traditional: Bank's balance sheet absorbs defaults
- P2P: Individual investors bear default risk directly

Disintermediation creates value only if the platform solves information problems as well as the bank did.

How Does a P2P Loan Go from Application to Repayment?



Process and information problem mapping:

1. **Application:** Borrower submits data
2. **Assessment:** Platform evaluates creditworthiness (addresses *adverse selection*)
3. **Risk grading:** Transparent risk categories
4. **Listing:** Loan posted for funding
5. **Funding:** Investors choose loans
6. **Disbursement:** Platform transfers funds
7. **Monitoring:** Track payments, handle defaults (mitigates *moral hazard*)

Key insight: Each step addresses a specific information problem identified in Section 1.

Each step in the P2P process addresses a specific information problem.

Is Cutting Out the Bank Worth the Extra Risk?

Strengths (solving information problems):

- **Lower costs:** No branch network
- **Better rates:** Savings passed to users
- **Transparency:** Detailed borrower data, clear risk grades
- **Diversification:** Investors spread across many loans
- **Financial inclusion:** Serves "thin-file" borrowers excluded by banks
- **Speed:** Automated underwriting (addressing adverse selection faster)

Examples: LendingClub, Prosper (US); Zopa, RateSetter (UK); Funding Circle (SME focus).

Risks (information problems remain):

- **Credit risk:** Investors bear all default losses
- **Liquidity risk:** Cannot easily exit before loan matures
- **Platform risk:** Platform failure disrupts servicing
- **Regulatory uncertainty:** Evolving rules
- **Adverse selection:** If assessment is weak, lemon problem persists
- **Moral hazard:** Borrowers may misuse funds
- **Concentration risk:** Small investor base or narrow loan types

Fundamental tension: Lower costs vs. higher risk exposure for investors.

P2P lending shifts risk from the bank's balance sheet to individual investors.

How Much Regulation Should Replace Market Discipline?

Regulatory approaches vary by jurisdiction:

European Union:

- **European Crowdfunding Service Providers (ECSP) Regulation** (2021): Harmonized framework for crowdfunding, including P2P lending
- Requirements: Authorization, disclosure, risk warnings, limits on unsophisticated investor exposure
- Goal: Balance innovation with investor protection

Switzerland:

- **FINMA oversight:** P2P platforms may need banking or securities dealer licenses depending on structure
- Emphasis on **client segregation** (investor funds separate from platform assets)
- Anti-money laundering (AML) compliance

Key policy question:

- How much should regulation substitute for market discipline?
- Too little: Investors may suffer losses due to platform failures or fraud
- Too much: Regulatory costs may eliminate the cost advantage of disintermediation

Regulation protects investors but may also limit the very disintermediation that creates value.

How Does a Three-Digit Number Decide Your Financial Future?

A single three-digit number determines whether you get a mortgage, a car loan, or a credit card. But 1.7 billion adults worldwide have no credit history at all.

How credit bureaus solve adverse selection:

- Collect and aggregate repayment history across multiple lenders
- Reduce information asymmetry by revealing past borrower behavior
- **Credit score:** Numerical summary of creditworthiness (e.g., FICO score: 300–850)

FICO score components (traditional approach):

- **Payment history (35%):** On-time payments signal reliability
- **Amounts owed (30%):** High credit utilization signals risk
- **Length of credit history (15%):** Longer history provides more data
- **New credit (10%):** Frequent applications signal distress
- **Credit mix (10%):** Diverse types (mortgage, credit card) signal experience

Limitations:

- **Thin-file borrowers:** Young people, immigrants, cash-based economies have no credit history
- Excludes alternative indicators of creditworthiness (rent payments, utility bills, education)

Traditional scoring works well for established borrowers but excludes millions with no credit history.

Can Your Phone Usage Predict Whether You'll Repay a Loan?

Alternative data sources:

- **Transactional data:** Bank account flows, spending patterns
- **Utility & rent payments:** Demonstrate payment discipline
- **Social media & behavioral data:** Network analysis, online activity (controversial)
- **Mobile phone usage:** Payment history, communication patterns

Machine learning in credit assessment (conceptual):

- **Pattern recognition:** ML models identify complex relationships between data and default risk
- **Non-linear relationships:** Traditional scoring uses linear weights; ML captures interactions
- **Continuous learning:** Models update as new repayment data arrives
- Applications: More accurate risk pricing, inclusion of previously "unbankable" borrowers

Fairness and bias concerns:

- ML models may *amplify* historical discrimination embedded in training data
- **Fairness-accuracy tradeoff:** More accurate models may be less fair; fairer models may be less accurate
- Regulatory scrutiny: EU AI Act, US Fair Lending laws

ML can improve accuracy but may amplify historical discrimination – the fairness-accuracy tradeoff.

What Are the Three Ways Machines Learn from Financial Data?

Theory: ML models fall into three categories based on how they learn from data.

Type	Learning Method	Finance Application	Example Algorithm
Supervised	Learns from labeled input-output pairs	Classification: default/no-default Regression: credit score prediction	Logistic regression Random forest
Unsupervised	Finds patterns without labels	Clustering: customer segmentation Anomaly detection: fraud, AML	k-means Isolation forest
Reinforcement	Trial-and-error	Trading strategies, dynamic pricing	Q-learning

Key distinctions:

- **Supervised:** Needs historical outcomes (e.g., past defaults) to train—most common in credit
- **Unsupervised:** Discovers hidden structure—ideal when labels are scarce or expensive
- **Reinforcement:** Learns optimal sequences of actions—suited for dynamic portfolio rebalancing

These three learning paradigms cover all ML applications in finance—each solves a different type of problem.

What Does the Journey from Raw Data to Credit Decision Look Like?

Theory: A data-driven lending decision follows an end-to-end pipeline from raw data to credit decision.

Pipeline stages:

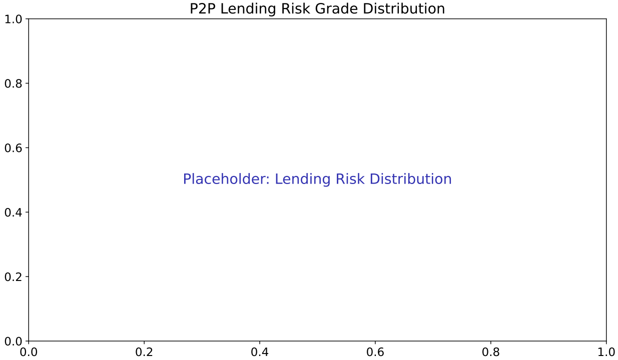
1. **Data collection:** Traditional (income, employment) + alternative (mobile, social, transactional)
2. **Feature engineering:** Transform raw data into predictive variables
   - Income stability: variance of monthly deposits
   - Spending patterns: ratio of essential vs. discretionary spending
   - Digital footprint: device type, browsing behavior (controversial)
3. **Model training:** Fit ML model to historical loan outcomes
4. **Model validation:** Test on held-out data; backtesting on past periods
5. **Deployment:** Real-time scoring via API (decision in seconds)
6. **Monitoring:** Detect model drift; fairness audits

Model drift: Data distributions change over time (e.g., COVID changed spending patterns, making pre-COVID models unreliable). Continuous retraining required.

Regulatory checkpoint: Models must be explainable (EU AI Act, US Fair Lending laws).

A model is only as good as its features—feature engineering is where domain knowledge meets data science.

How Do Risk Grades Translate to Returns for Investors?



Interpreting the risk-return distribution:

- **Risk grades (A–G):** Platform assigns based on credit assessment
- **Higher grades → lower default rates, lower interest**
- **Lower grades → higher default rates, higher interest**
- Investors choose exposure based on risk tolerance

Diversification across risk grades:

- Spreading \$10,000 across 100 loans of \$100 each reduces idiosyncratic (loan-specific) risk
- Systematic risk (economic downturn affecting all borrowers) remains
- Connection to Section 4: Portfolio theory in action

Diversification across risk grades is a practical application of the portfolio theory in Section 4.

Why Do Higher Returns Always Come with Higher Risk?

You could put your money in a Swiss government bond and earn 1% — guaranteed. Or you could buy a tech stock and earn 50% — or lose 30%.

Core principle: Higher expected returns come with higher risk.

Defining risk:

- **Risk = variability** of returns (uncertainty about outcomes)
- **Safe asset:** Narrow range of possible returns (e.g., Swiss government bond: 0.5%–1%)
- **Risky asset:** Wide range of possible returns (e.g., technology stock: −30% to +50%)

Why do investors accept risk?

- **Risk premium:** Compensation for bearing uncertainty
- Example: Stocks historically return 7% annually; government bonds 2%. The 5% difference is the equity risk premium

Diversification intuition:

- Holding multiple risky assets can reduce overall portfolio risk
- The key: Assets must not move in perfect lockstep
- Foundation for modern portfolio theory (next section)

Visual intuition: Safe (narrow bell curve) vs. Risky (wide bell curve).

This risk-return tradeoff is the most fundamental concept in all of finance.

How Can Combining Risky Assets Reduce Overall Risk?

Classic example:

- **Umbrella company:** Profits when it rains, loses when sunny
- **Sunscreen company:** Profits when sunny, loses when it rains
- **Portfolio of both:** Stable returns regardless of weather

Correlation:

- **Perfect positive correlation (+1):** Assets move together (no diversification benefit)
- **Perfect negative correlation (-1):** Assets move in opposite directions (maximum diversification benefit)
- **Zero correlation (0):** Assets move independently (some diversification benefit)

Real-world diversification:

- Spread investments across asset classes (stocks, bonds, real estate, commodities)
- Within stocks: Different industries, geographies
- Within bonds: Different maturities, credit qualities

Foundation of Modern Portfolio Theory (MPT):

- Harry Markowitz (1952): Formalized diversification mathematically
- Nobel Prize in Economics (1990)

Harry Markowitz won the Nobel Prize for formalizing this simple intuition.

Can an Algorithm Give Better Financial Advice than a Human?

Your financial advisor recommends a fund. It happens to be the one that pays them the highest commission. What if the advisor had no commission incentive — because the advisor was an algorithm?

Definition: A **robo-advisor** is an automated digital platform that provides financial planning and investment management services with minimal human intervention.

Addressing the principal-agent problem:

- Traditional human advisors may recommend high-commission products (conflict of interest)
- Robo-advisors use algorithms, eliminating commission-based incentives
- Transparency: Clients see exactly what they're invested in and why

Typical robo-advisor process:

1. **Questionnaire:** Risk tolerance, time horizon, financial goals
2. **Risk profile:** Conservative, moderate, or aggressive
3. **Asset allocation:** Algorithm assigns percentages to asset classes
4. **Automated rebalancing:** Maintains target allocation over time
5. **Tax optimization:** Tax-loss harvesting (selling losers to offset gains)

Key platforms: Betterment, Wealthfront (US); Scalable Capital (EU); True Wealth, Selma Finance (Switzerland).

Robo-advisors reduce conflicts of interest by removing commission-based incentives.

How Do Robo-Advisors Build an Optimal Portfolio?

Modern Portfolio Theory (MPT) – Harry Markowitz (1952):

- Formalizes the diversification intuition from Frame 11
- Goal: Maximize expected return for a given level of risk (or minimize risk for a given expected return)
- **Efficient frontier:** The set of optimal portfolios offering the highest expected return for each risk level

Asset allocation:

- **Strategic allocation:** Long-term target mix (e.g., 60% stocks, 40% bonds)
- **Tactical allocation:** Short-term adjustments based on market conditions (less common in robo-advisors)
- Most robo-advisors use **passive investing** with low-cost index funds or ETFs (Exchange-Traded Funds)

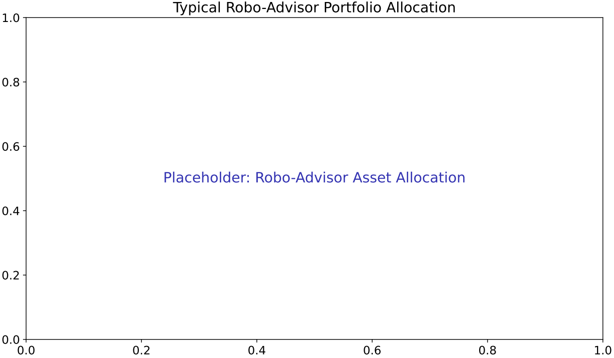
How robo-advisors implement MPT:

- Use historical return and correlation data to estimate the efficient frontier
- Map client risk tolerance to a point on the efficient frontier
- Construct a portfolio using diversified, low-cost ETFs
- Automatically rebalance when allocations drift beyond thresholds (e.g., 5%)

Key insight: Robo-advisors democratize access to sophisticated portfolio optimization previously available only to wealthy clients.

MPT formalizes the diversification intuition from Frame 11 into an optimization problem.

What Does a Conservative vs. Aggressive Portfolio Look Like?



Interpreting allocation profiles:

- **Conservative:** High bond allocation (70–80%), low volatility, suitable for near-term goals or risk-averse investors
- **Moderate:** Balanced (50–60% stocks), medium risk, typical for mid-term goals
- **Aggressive:** High stock allocation (80–90%), high volatility, suitable for long-term goals and risk-tolerant investors

Fee advantage:

- Robo-advisors: 0.25–0.50% annually
- Traditional advisors: 1–2% annually
- Over 30 years, a 1% annual fee difference can reduce wealth by 25% due to compounding

The fee difference compounds dramatically over decades – 1% annual fee can reduce wealth by 25% over 30 years.

When Should You Choose a Robot Over a Human Advisor?

Dimension	Robo-Advisor	Traditional Advisor
Cost	Low (0.25–0.5%)	High (1–2%)
Minimum investment	Low ($500–$5,000)	High ($50,000+)
Human interaction	Minimal / on-demand	Ongoing relationship
Customization	Standardized portfolios	Highly tailored
Tax optimization	Automated tax-loss harvesting	Manual, advisor-dependent
Conflicts of interest	Low (algorithm-driven)	Potential (commission-based)
Behavioral coaching	Limited / automated nudges	High (emotional support)
Complex planning	Limited (estate, trusts)	Comprehensive

Hybrid model:

- Combines algorithm-driven portfolio management with access to human advisors for complex questions
- Examples: Vanguard Personal Advisor Services, Schwab Intelligent Portfolios Premium
- Swiss platforms: True Wealth, Selma Finance offer hybrid features

The hybrid model – algorithm plus human access – may offer the best of both worlds.

Do the Same ML Techniques Power All Financial Functions?

We've seen ML applied to credit scoring and portfolio optimization. The same three techniques — classification, clustering, anomaly detection — power every financial function.

Theory: The same ML techniques apply across *all* financial functions—not just lending.

Financial Function	**Data-Driven Approach**	**ML Technique Used**
Payments	Fraud detection	Supervised classification
Lending	Credit scoring, segmentation	Supervised + unsupervised
Insurance	Risk pricing, claims prediction	Regression, classification
Investment	Portfolio optimization, sentiment	RL, NLP
Compliance	Transaction monitoring	Anomaly detection

Cross-cutting insight: The same techniques—classification, clustering, anomaly detection—are reused across functions. What changes is the *data* and the *business context*.

The data flywheel:

- More users → more data → better models → better service → more users
- This creates winner-take-most dynamics and natural monopoly tendencies
- Regulatory response: data portability (PSD2, Open Banking) to prevent data lock-in

Data-driven approaches are not limited to lending—every financial function benefits from the same ML toolkit.

Is Data Replacing Banks as the Financial Middleman?

Synthesis: A unified data-driven approach to information problems.

P2P lending and robo-advisors solve the same problems traditional intermediaries solve, but with data instead of branches:

Information Problem	Traditional Solution	Data-Driven Solution
Adverse selection (lending)	Relationship lending, collateral	Alternative data, ML scoring
Moral hazard (lending)	Monitoring, covenants	Automated tracking, alerts
Principal-agent (advisory)	Fiduciary duty, reputation	Algorithm transparency
Diversification (advisory)	Advisor expertise	MPT, automated rebalancing

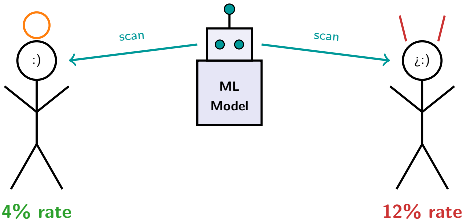
Connection to Python prerequisite:

- Data manipulation (pandas): Cleaning credit bureau data, financial time series
- Visualization (matplotlib, seaborn): Risk-return charts, allocation pie charts
- Statistical modeling (scikit-learn): Credit scoring models, portfolio optimization

Fundamental insight:

- Data-driven approaches do not *eliminate* information problems
- They solve them *more cheaply* by replacing physical infrastructure with algorithms
- Value creation depends on whether the platform matches or exceeds the traditional intermediary's information processing

Data-driven approaches do not eliminate information problems – they solve them more cheaply.



Algorithms can't eliminate risk — but they can price it.

Summary

Four key takeaways from Lesson 03:

1. **Information problems are fundamental:**
   - Adverse selection (before transaction), moral hazard (after transaction), and principal-agent problems explain why financial markets need intermediaries
   - Technology does not eliminate these problems – it addresses them differently
2. **P2P lending disintermediates but shifts risk:**
   - Lower costs and better rates for both sides when platforms solve information asymmetry effectively
   - Investors bear credit risk directly (no bank balance sheet protection)
   - Alternative data and ML improve credit assessment but raise fairness concerns
3. **Robo-advisors democratize portfolio optimization:**
   - Automated implementation of Modern Portfolio Theory at low cost
   - Reduce principal-agent conflicts inherent in commission-based advisory
   - Hybrid models combine algorithmic efficiency with human behavioral coaching
4. **Data is the new intermediary:**
   - Both P2P lending and robo-advisory replace physical infrastructure (bank branches, advisor offices) with data processing
   - Value creation depends on solving information problems as well as or better than traditional intermediaries, but more cheaply

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Next lesson: RegTech and Compliance – how technology automates the regulatory response to these information problems.