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ABSTRACT OF THE DISSERTATION

Essays in Financial Economics

by

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Professor Andrea Lynn Eisfeldt, Chair

In the first chapter, I propose that the nonfinancial component of financial firms' assets, in particular the growth opportunities associated with business operations, drives most of the variation in their equity valuation. I document this fact for a large class of intermediaries: life insurance companies. In particular, I decompose insurers' market equity returns into net financial asset returns and net business asset returns and show that these two components have very different risk exposures and are negatively correlated outside of the 2008-2009 financial crisis. The variation in life insurers' net business asset returns drives 81% of the aggregate time series variation and 100% of the cross-sectional variation in their market equity returns. For this reason, the current intense regulation on life insurers' net financial assets may be insufficient as a great deal of risk is derived from their net business assets which are comparatively under-regulated.

In the second chapter (with Andrea Eisfeldt), we review the advances in the literature studying the causes and consequences of capital reallocation (or lack thereof). Capital reallocation is procyclical, despite measured productive reallocative opportunities being acyclical, or even countercyclical. We provide a comprehensive set of capital reallocation stylized facts for the US, and an illustrative model of capital reallocation in equilibrium. We relate capital reallocation to the broader literatures on business cycles with financial frictions, and on resource misallocation and aggregate productivity. Finally, we provide directions for future research. This article has been published in Annual Review of Financial Economics.

The dissertation of Yu Shi is approved.

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2021

*To my loving parents, Jianwei and Xiaohui, for their support and encouragement from day one.*

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# CHAPTER 1

# The Nonfinancial Value of Financial Firms

## 1.1 Introduction

Financial intermediaries, such as banks and life insurers, are major systemic players in the economy and are under intense regulatory scrutiny. In particular, regulators monitor the risks derived from financial firms' asset portfolios closely, so as to safeguard against the possibility of default. As a result, banks and insurers mostly hold safe fixed-income products and their marked-to-market asset portfolios have CAPM betas that are close to 0. Despite of the seemingly safe financial assets they hold, their market equities are still volatile and have CAPM betas that exceed 1. This puzzling evidence is first documented by Begenau and Stafford [2019] for banks, while as illustrated in Figure 1.1, it is also true for life insurers. Understanding what drives the volatile equity valuation of financial firms, in particular the high CAPM betas, is important for designing optimal regulation. In this paper, I show that financial firms' nonfinancial business operations drive most of the variation in their market valuation and should also be subject to regulatory scrutiny to avoid potential insolvency in recessions.

In addition to implications to the regulation of financial firms, the fact that the nonfinancial business operations drive most of the variation in financial firms' market equity returns also has important application to intermediary asset pricing. The empirical literature on intermediary asset pricing considers intermediaries as marginal investors and uses shocks to their leverage ratio to price assets in the cross section (e.g., He, Kelly, and Manela [2017] and Adrian, Etula, and Muir [2014]). However, I demonstrate that the nonfinancial component exhibits pricing power even for the asset classes in which the financial firms are not marginal. My results provide a new view on understanding the role of intermediaries in the economy.

Financial firms' equity returns can be decomposed into two parts: the net financial asset returns and the net business asset returns. The value of net financial assets is defined as the value of marked-to-market financial assets in excess of liabilities, and it accounts for 60% of financial firms' market equity valuation. The value of net business assets is then defined as the remaining 40% that comes from the nonfinancial component of financial firms. Examples of the sources of net business assets are (1) asset management skills, (2) government guarantees, and (3) growth opportunities associated with business operations, where business operations are defined as non-investment profit-generating activities. For example, business operations include collecting deposits and writing loans for banks, and selling insurance products for insurance companies. In this paper, I argue that most of the variation in financial firms' market equity returns is driven by the variation in their net business asset returns, and the key component of their net business assets is business operations.

For the main analysis of the paper, I focus on a large financial sector with the most comprehensive data available: the life insurance sector, and use it as a representative financial sector to study the nonfinancial component of financial firms. Life insurers are natural candidates to study this question for two reasons. First, they are a large class of intermediaries and hold 7.6 trillion dollars of assets as of 2018, which is two times the assets that are held by broker dealers and roughly 50% of the assets held by commercial banks. In addition, they are also the largest corporate bond holders in the U.S. and hold 40% of the market. Second, regulations mandate that insurers must file detailed business activity data and portfolio holding data. The richness of the data makes it possible to study micro-level business operations and mitigates the empirical measurement errors of asset holdings.

I first document that life insurers' aggregate net financial assets and their aggregate market equity have very different risk loadings. As major fixed-income investors, life insurers' net financial asset returns are highly exposed to the *credit market*. However, their market equity is highly exposed to the *equity market* with CAPM betas exceeding one. In addition, insurers' market equity yields zero or negative loadings on the credit market after controlling for the equity market risk. This suggests that the variation in insurers' net business asset returns is key to understand the variation in their market equity returns. In fact, in the aggregate time series, the variation in insurers' net business asset returns is able to explain 81% of the variation in their market equity returns. This evidence is also true in the cross-section. Although the risk loadings of insurers' market equities vary a lot across firms, there is little cross-sectional variation in the risk loadings of their net financial assets. The variation in net business asset returns essentially explains 100% of the variation in life insurers' market equity returns in the cross section.

I then demonstrate that the variation in insurers' net business asset returns is driven by their business operations. I first show that life insurance companies actively manage their business operations. Using detailed data on the breakdown of business operation cash flows, I document that insurers' business operation profits are pro-cyclical. I provide suggestive evidence that the cyclicality is a result of simultaneous demand and supply shocks. In addition, I show that insurers offload investment risks and other non-market related risks from outstanding insurance policies to new customers through sales of new insurance products. I then demonstrate that most of the unexpected shocks to insurers' net business asset returns are derived from business operations. In particular, I decompose insurers' unexpected net business asset returns into business-cash-flow news and expected-business-return news using a vector auto regression (VAR) model following Vuolteenaho [2002]. I show that at least 74% of the cross-sectional variation in net business asset returns is driven by future business-cash-flow shocks. Moreover, the model implied business-cash-flow shocks to insurers are highly correlated with the cash-flow shocks to the market portfolio, providing an explanation for the high equity CAPM betas.

Other sources of net business assets, such as asset management value, are less likely to drive such a large variation in net business asset returns. Using detailed CUSIP level holding data and textual analysis, I demonstrate that insurers create little trading value. I calculate investment returns for a wide range of asset classes using the portfolio position of each insurer. I find that life insurance companies are passive investors; their portfolios yield similar returns to a combination of (levered) fixed-income indices and they rarely adjust portfolio weights across asset classes.

The remainder of the paper proceeds as follows. Next I show how my findings relate to existing literature. Section 1.2 introduces the institutional details on the life insurers and the data used. In Section 1.3, I document primary empirical evidence regarding the risk exposure differences between financial and business asset returns. I study insurers' net business asset value in Section 1.4, and discuss other possible sources of net business assets in Section 1.5. Section 1.6 discusses the applications of the net business asset returns, while Section 1.7 provides my conclusions

**Related Literature** This paper relates to the literature discussing the facts that financial firms' market equity valuation are very different from their net financial assets. Begenau, Piazzesi, and Schneider [2015] find that a two factor model with interest rate risk and credit risk is able to explain 70% of the asset risk exposure. However, they also determine that banks' equity has a market beta of almost one, which is a type of risk not introduced by their asset holdings. Begenau and Stafford [2019] confirm that banks don't have any edge in investments but their market equity seems volatile. Falato, Iercosan, and Zikes [2019] use detailed high frequency regulatory data to demonstrate that banks' investments are highly exposed to the equity market prior to 2014. Minton, Stulz, and Taboada [2017] find that banks with more trading assets are worth less. Drechsler, Savov, and Schnabl [2018] argue that banks' market power of deposit franchise is able to explain the different term structure risk exposure between their financial assets and market equity. Chodorow-Reich, Ghent, and Haddad [2020] find that the risk pass-through from life insurers' assets to equity is small. They argue that insurers act like insulators and are able to hold assets for the long term. In this paper, I focus on studying the properties of net business assets and apply the variance decomposition in Campbell [1991] and Vuolteenaho [2002] to financial firms to decompose the variance of net business asset returns.

This paper also relates to a large body of work regarding the valuation of financial firms. Keeley [1990] discusses how franchise value created by deposit insurance influences banks' valuations. Sarin and Summers [2016] and Chousakos and Gorton [2017] relate banks' valuations to franchise value in the post financial crisis period. Begenau, Bigio, Majerovitz, and Vieyra [2019] argue that book accounting is slow to acknowledge loan losses, and that Q can predict future profitability. Egan, Lewellen, and Sunderam [2017] determine that the variation in deposit productivity explains the majority of variation in bank value. One recent explanation for the change of banks' valuation post financial crisis is the loss of government guarantees (e.g. Atkeson, d′Avernas, Eisfeldt, and Weill [2019], Berndt, Duffie, and Zhu [2019]). I introduce a new channel regarding the valuation of life insurers and argue that variation in the value of business operations is the most important channel in terms of explaining life insurers' market equity variation.

My work also relates to the study on financial firms' active business operations. Meiselman, Nagel, and Purnanandam [2020] confirm that banks' accounting profitability predicts tail risks. Paravisini, Rappoport, and Schnabl [2015] posit that banks' operation specialty makes credit difficult to substitute. This has consequences for competition in the credit markets and the transmission of credit shocks to the real economy. Wang, Whited, Wu, and Xiao [2020] find that bank market power explains much of the transmission of monetary policy to borrowers. In the case of insurers, Koijen and Yogo [2015] and Koijen and Yogo [2016] discuss insurers' regulatory arbitrage in the product market and Ge [2017] studies the spill over pricing effect within same insurance group across different product types. My paper provides new evidences for life insurers that they manage their business operations to smooth out their book equity. I also focus on linking life insurers' active business operations to their market equity valuation.

The discussion on asset management value is related to topics regarding the trading behaviors of insurers. Becker and Ivashina [2015] determine that insurers reach for yield within the regulatory framework. Ellul, Jotikasthira, Lundblad, and Wang [2015] posit that accounting rules affect life insurers' trading behavior. Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner [2018] document the reaching for yield behavior caused by the variation in the liability structure among life insurance firms. Ge and Weisbach [2019] suggest that shocks to insurers' business operations lead them to hold safer portfolios. Timmer [2018] finds insurance companies trade counter cyclically such that they buy when returns have been negative and sell after high returns. I provide new evidence on understanding the asset management value of insurers using detailed asset holding data and show that they are passive index holders.

Finally, my work relates to the literature on intermediary asset pricing. Motivated by the theoretical literature on intermediaries (e.g., He and Krishnamurthy [2013], Brunnermeier and Sannikov [2014] and Brunnermeier and Pedersen [2009]), empirical work uses measure of the marginal value of the wealth of intermediaries as an informative stochastic discount factor (SDF) to determine asset prices in the cross section (e.g., Adrian, Etula, and Muir [2014], He, Kelly, and Manela [2017] and Kargar [2018]). In particular, He, Kelly, and Manela [2017] find that shocks to the equity capital ratio of primary broker-leaders possess significant explanatory power for the cross-sectional variation in expected return for a variety of asset classes. My work provides an alternative theory for the sources of the pricing power that the capital ratio is able to price different asset classes for different reasons: net financial asset returns and net business asset returns exhibit pricing power for different asset classes.

## 1.2 Background on Life Insurers and Data

I study all publicly traded life insurers in the U.S., identified by the Standard Industrial Classification (SIC=631) and the SNL financial industry definition. Most public insurers have multiple subsidiaries that file under different entity names with the National Association of Insurance Commissioners (NAIC). To ensure that the data is aggregated at the publicly traded parent firm level, I manually create a historical linking table that manages the survivorship bias from the historical events when some subsidiaries went out of business and addresses the fact that some of the subsidiaries may be traded between life insurance companies over time. My main sample includes 39 public insurers in the U.S. that are consolidated by 227 unique subsidiary entities from 2000 to 2018.[1] Panel A of Table 1.2 provides the summary statistics for key financial variables of these firms. An average life insurer has 5.9 subsidiaries and holds 93.56 billion in assets. They contain little long-term debt, and have an average market leverage of 13.56. Together, these 39 firms account for 40% of the total book assets of the entire life insurance sector.

I now introduce the details for measuring insurers' assets and equities. As stated in the introduction, life insurers' equity valuation ($E$) can be decomposed into the value of net financial assets ($E^{Fin}$) and the value of net business assets ($E^{Bus}$). This equality can be expressed in terms of their respective returns as follows:

$$R^E = \frac{E^{Fin}}{E} R^{Fin} + \frac{E^{Bus}}{E} R^{Bus}. \tag{1}$$

If not stated otherwise, I use net financial asset return to denote the scaled net financial asset return ($R^{Fin}E^{Fin}/E$) and net business asset return to denote the scaled net business asset return ($R^{Bus}E^{Bus}/E$) for simplicity. The goal of the empirical analysis is to study net business asset returns by measuring the difference between the market equity returns and net financial asset returns. insurers' market equity returns are easy to be measured using public equity market data. To understand the variation in net financial asset returns, the starting point is to grasp the accounting framework of insurers.

### 1.2.1 Net Financial Assets and Returns

**Accounting Framework** I first introduce the components of net financial assets. The asset side of insurers' balance sheets consists of financial investments ($A^I$) while the liability side consists of the business obligations to policy holders ($Pol$) and the financial obligations to debt holders ($D$). Figure 1.3 illustrates a simplified balance sheet for insurers. The value of net financial assets ($E^{Fin}$) is defined as the difference between the financial investments

[1] A complete list of the life insurance companies studied in this paper is provided in Appendix 1.9.1.

and the value of outstanding liabilities:

$$E^{Fin} \equiv A^I - Pol - D. \tag{2}$$

I discuss the components of life insurers' financial investments and business obligations by providing an example of the breakdown of assets and liabilities of Metlife's general account for their largest subsidiary (NAIC Code 65978) as of the end of 2019 in Table 1.1.[2] Financial investments ($A^I$) reported at fair value account for 96% of the total assets. The total financial investments are divided into 6 main categories: (1) fixed-maturity securities, (2) equities, (3) mortgage loans, (4) real estate, (5) cash and other short term investments, and (6) other invested assets. The fixed-maturity securities can be further divided into finer categories: (1) treasury securities, (2) agency-backed MBS, (3) municipal securities, (4) loans, and (5) corporate bonds. "Other invested assets" primarily consist of derivatives, joint ventures, and other affiliated investments. The fair value is reported as the market value for publicly traded financial assets and as the theoretical model value for financial assets that are privately placed. Metlife states in their financial filings that the fair value of a financial asset is determined as follows. For publicly traded securities, the market price is determined by one of three primary sources of information: quoted market prices in active markets, independent pricing services, or independent broker quotations. For privately placed securities, the fair value is determined considering one of three primary sources of information: market standard internal matrix pricing, market standard internal discounted cash flow techniques, or independent pricing services. Mortgage loans are stated at the unpaid principal balance, while real estate is stated as the lower of the carrying value or the fair market value.

Business liabilities that are related to outstanding policies ($Pol$) account for 82% of the

[2]Insurers segregate their financial reporting into general account assets which back fixed rate liabilities and death benefits, and separate account that are linked to variable rate products. As gains and losses on separate account assets are mostly a direct pass-through to policyholders, I focus the analysis on general accounts. This is consistent with the literature studying life insurers' trading behavior such as Chodorow-Reich, Ghent, and Haddad [2020].

total liabilities. The business liabilities can be regrouped into: (1) policy related balances (denoted by reserve) and (2) payables for insurance related costs. Policy related balances consist of reserve for life contracts, accident and health contracts, annuity contracts (deposit type), and policyholder dividends. As insurance policies essentially have no exposure to market risk, finance theory implies that the market value of these policies is determined by the term structure of riskless interest rates. However the book value of business liabilities is recorded using a mechanical regulatory discount rate and is not marked-to-market. Section 1.2.2 provides detailed discussions on adjustments on the book value of insurers' business liabilities to reflect their market value.

As investments and business liabilities are a significant part of assets and liabilities, the primary analysis of this paper focuses on these two main components, and assumes that assets are 100% investments and liabilities, apart from outstanding debt, are 100% business related. In addition to the fact that investments and business policies are the biggest components, another implicit assumption is that they are volatile and drive most of the variations in assets and liabilities.

Following Equation 2, the net financial asset return can be expressed with the respective scaled returns to the components of the net financial assets. I denote the investment return as $R^I$, the debt interest rate as $R^D$, and the policy interest rate as $R^L$. The net financial asset return is then:

$$R^{Fin} = \frac{A^I}{E^{Fin}} R^I - \frac{D}{E^{Fin}} R^D - \frac{Pol}{E^{Fin}} R^L. \tag{3}$$

The data used to calculate investment returns is introduced in Section 1.2.1 and the data used to calculate policy interest rates is introduced in Section 1.2.1.

**Investment Holdings and Returns** In this section, I provide details regarding the data used to measure investment return $R^I$. I collect CUSIP level data for insurers' portfolio holdings of various asset classes at annual frequency. Holdings for long term fixed-income assets are collected from the Schedule D in the statutory filings. I classify these holdings into four major fixed-income asset classes: corporate bonds, agency-backed MBS, treasuries, and municipal bonds by applying textual analysis to the description of each asset. The details on textural analysis are provided in Appendix 1.9.2. In addition to fixed-income assets, I also collect holdings for loans, mortgages, equities, and cash equivalents.[3] Panel B1 of Table 1.2 reports the portfolio weights for each trading financial asset class (i.e., corporate bonds, agency-backed MBS, treasuries, municipal bonds, equities and cash equivalents). Life insurance companies hold diversified investment portfolios at the parent firm level; the average public life insurance company holds 3,000 different securities, and 73% of which are invested in the corporate bond market. Cross-sectionally, there is not much heterogeneity in asset class weights. Panel B2 of Table 1.2 provides information concerning the mortgage loan portfolios. For the median firm in the firm-year panel, almost 100% of their mortgage loans are in good standing. The distribution is highly skewed and the skewness is driven by intense defaults on mortgages during the financial crisis.

The investment portfolio return for firm $i$ at time $t$ is calculated as follows:

$$R^I_{i,t} = \sum_{k \in I} \omega_{i,t-1,k} R_{i,t,k},$$

where $\omega_{i,t-1,k}$ is the value weight for asset $k$ held by firm $i$ at $t-1$ and $R_{i,t,k}$ is the asset return for asset $k$ for time $t$. The value weights are calculated using the fair value reported in insurers' statutory filings for each asset.

In the main analysis, I calculate investment return at a quarterly frequency, using only assets that are publicly traded during the period holding the asset position constant over the course of a year. This return series includes corporate bonds, treasuries and equities whose CUSIP can be merged into the BofAML corporate bond indices, TRACE, Bloomberg, or CRSP. Security return is collected from the aforementioned databases, and the market value

[3] Mortgage loan holdings are collected from Schedule B, equities are collected from Part 2 of Schedule D, and cash equivalents are collected from Schedule E.

of the securities held in the portfolio is collected from the filings. For cases where a bond matures during any given quarter, I denote the quarterly return as the product of the yield to maturity up to the maturity date and the corporate bond index return for the rest of the quarter. This measure exhibits the most accurate pricing information. However, other than corporate bonds and equities, prices for other asset classes are largely unavailable.

As a robustness check and to fully utilize the data from insurers' statutory filings, I also calculate the annual return series for the insurers' entire investment portfolio. This return series include corporate bonds, treasuries, municipal bonds, MBS, equities, mortgage loans and cash equivalents. For any securities other than mortgage loans whose return is not provided by data vendors, I infer their return from the statutory filings. In addition to fair values, insurers also report securities' clean market price ($P$), coupon payments ($CP$), and accrued interests ($Acc$). The return of security $j$ at time $t$ is:

$$R_{j,t} = \frac{P_{j,t} + Acc_{j,t} + CP_{j,t}}{P_{j,t-1} + Acc_{j,t-1}}.$$

If different insurers have the same assets in their portfolio and report different return, I take the median of all the reported returns for the same asset in a given year. I cross check the inferred returns for the securities that have available return data. A regression having the inferred return as dependent variables and the actual market return collected from the data vendors as independent variables yields a coefficient of 0.99 and a R square of 0.85. I conclude that the returns inferred from the filing are close to the actual returns despite some concerns with the fact that insurers may purposely report higher return for the assets that are not publicly traded. The cross-check details are provided in Appendix 1.9.3.

The calculations of mortgage loan return is much more complicated and, as such, the details are omitted from the main paper, but are provided in Appendix 1.9.4.

**Policy Interest Rates** As discussed in previous sections, the book value of policies, denoted as reserve, is not marked-to-market. Instead, they follow a mechanical regulatory discount rate that is set at the time of the sale and is fixed over the life of the policies. Thus, policy interest rates can not be directly measured using accounting data on policy interest. Instead, I use returns of treasury indices with different maturities as proxies for policy interest rates, as insurance policy liabilities are largely exposed to risk-free term structure risks. The goal of finding a proper proxy is to rule out the pass-through effect from insurers' liabilities to market equities and to measure policy interest rates accurately. Thus, the most conservative measure would be the one with largest credit market exposure and most negative equity market exposure. Table 1.3 reports the risk exposures (risk factor construction is explained in Section 1.2.3) for treasury index returns with different maturities. Details regarding the constituents of the treasury indices are introduced in Appendix 1.9.5. Not surprisingly, the treasury index returns are all exposed to fixed-income risk factors. In addition, they also have positive loadings on the credit factor and negative loadings on the equity market factor. As the index for treasuries whose maturities are between five and seven years has the most significant loadings on the credit market and the equity market, it is used as a proxy to policy interest rates for the remainder of the paper. In addition to being a conservative measure, using treasury index with five to seven years of maturities may also be the most accurate proxy to insurers' policies. Although insurers don't report the duration of their outstanding policies, they are explicit about using investment assets to hedge liabilities' duration risks and the average life insurer's investment portfolio has a duration of seven years. This is in line with my choice of the proxy. Finally, as the value of policies is not to marked-to-market as well, I set the policy value to their upper bound ($Pol/A^I = 1$), so that the scaling effect ($Pol/E^{Fin}$) provides the largest pass-through from liabilities to market equities.[4]

[4] This assumption provides the most conservative measure for policy returns' market exposure as long as life insurers' market leverage and book leverage are both acyclical, which is true empirically.

### 1.2.2 Net Business Assets and Returns

**Accounting Framework** The value of net business assets, by definition, is the difference between the value of market equities and the value of net financial assets as follows:

$$E^{Bus} \equiv E - E^{Fin}.$$

Denote the net business asset capital gain as $\Delta E^{Bus} \equiv \Delta E - \Delta E^{Fin}$, the net business asset return can then be written in two parts:

$$R^{Bus} = \frac{\Delta E^{Bus}}{E^{Bus}} + \frac{CF^{Bus}}{E^{Bus}}, \tag{4}$$

where the second term is the net profit made from insurers' business operations (henceforth business operation cash flows).[5] It can be interpreted as the net business asset dividends, which are "paid" to the net financial asset accounts when insurers invest their business operation cash flows into the financial market. Note that net business asset return is not necessarily greater than $-1$ as the value of net business assets is not necessarily positive. When the value of business operation growth opportunities is negative and the firm looks like a project with negative net present value, corporate theory would suggest the firm to liquidate. However, as most of the net financial assets in insurers' portfolios are somewhat illiquid, they will have to pay high liquidation cost to sell their assets. When the liquidation cost is higher than the absolute value of the negative business asset value, it is optimal to stay in business. Thus, it is possible for insurers to have a negative value for their net business assets (i.e., a business liability on net). Whenever $R^{Bus}$ is less than $-1$, the value of net business assets switches signs. This does not change any of the results and interpretation provided in this paper.

[5] Among all different types of net business assets, only business operations and asset management will potentially provide cash flows. The cash flows that come from asset management can be interpreted as the excess returns from insurers' investment portfolios (alpha). For insurers specifically, they do not have significant alpha and thus make the asset management cash flows empirically irrelevant.

I now introduce the components of insurers' business operation cash flows ($CF^{Bus}$). The profit associated with the net business assets is the premiums ($Prem$) collected from policy holders. The costs associated with the net business assets are benefits ($Ben$) paid as policy claims, increases in reserve ($\Delta Pol$), and operational expenses ($C$), such as commissions, general expenses and taxes.[6] The net profit of business operations can then be stated as:

$$CF^{Bus} = Prem - Ben - \Delta Pol - C. \tag{5}$$

Premiums can be further divided into premiums collected from new customers ($Prem^{New}$) and premiums collected from renewal policies ($Prem^{Old}$). Increases in reserve can also be further divided into reserve required due to sales of new products ($Pol^{New}$ ) and minus the reserve released by terminated products ($Pol^{Rel}$). Given the breakdown of premiums and increases in reserve, the net business asset dividend ($CF^{Bus}$) can be further grouped into: (1) net profit from new customers ($CF^{New}$), (2) net profit from existing customers ($CF^{Old}$), and (3) costs ($C$). The net profit made from new customers equals first time premiums net of reserve increased due to sales of new products ($CF^{New} \equiv Prem^{New} - Pol^{New}$), while the net profit made from existing customers is renewal premiums, net of benefits, plus released reserve due to the termination of products ($CF^{Old} \equiv Prem^{Old} - Ben + Pol^{Rel}$). In particular:

$$CF^{Bus} = \underbrace{Prem^{New} - Pol^{New}}_{CF^{New}} + \underbrace{Prem^{Old} - Ben + Pol^{Rel}}_{CF^{Old}} - C. \tag{6}$$

**Net Business Asset Dividends** In this section, I introduce the data sources used to calculate net business asset dividends and discuss the effects and adjustments on accounting variables that are not marked-to-market (denoted with a hat).

The premiums ($Prem$), benefits ($Ben$) and operation costs ($C$) are realized during the period and, as such, are trivially measured at their market value. The quarterly data for these variables are retrieved from the *Net Income Statements*. The annual breakdowns for

[6] General expenses include rents, salaries and wages, advertising etc.

premiums are collected from *Exhibit 1: Premiums and Annuity Considerations.*

On the other hand, increases in reserve ($\widehat{\Delta Pol}$) are not marked-to-market as insurers use the mechanical regulatory discount rates to record reserve. The quarterly data for increases in reserve is retrieved from the *Net Income Statements* and the annual breakdowns for increases in reserve are collected from the *Analysis of Increases in Reserve.* The new policy reserve ($\widehat{Pol^{New}}$) are recorded using the mechanical discount rate imposed by regulation at the time of sales. Despite the fact that they are not technically marked-to-market, the value of the required reserve is close to the market value as the mechanical discount rate is calculated using current market data. I adjust the new policy reserve to their market value using data provided by Koijen and Yogo [2017].[7] In particular, they calculate the ratio between the regulatory required reserve value and the market value of the policies sold at the policy level using detailed product data. I take the product-weighted average of this ratio to infer the market value of new policy reserve.[8] The policy reserve released $\widehat{Pol^{Rel}}$ can be studied in two separate cases. First, for policies that are not expected to mature during the current time period, the reserve released is different from the market value of the policy obligation released as there is a timing difference. Examples include death, surrender and lapsation related reserve. Although the released policy reserve is not marked-to-market, the difference between the reserve and market value is caused by imprecise model assumptions on longevity, surrender rate and lapsation rate. All of these are insurance specific risks and are not correlated with any market risks. In addition, for policies that are expected to mature during the current time period, released policy reserve is a flow term and reflects the true market value. In both cases, the differences between the net actual payouts ($Ben - Prem^{Old}$) and released policy reserve ($\widehat{Pol^{Rel}}$) simply reflect the insurance specific risks that are not

[7] https://www.openicpsr.org/openicpsr/project/112888/version/V1/view.

[8] The regulation adopts a different discount rate formula for life insurance products and annuities. For each firm-year, I use the ratio between their reserve for life insurance and annuities from last period as a proxy for product weights, and use the product weighted reserve-to-market ratio for adjustments. Although the reserve to market ratio is specific to each products due to differences in the payout structure, the time series average is able to capture the main difference of the market risk exposure in the regulatory discount rate and risk-free yield curve.

well captured in their actuarial model on cash flows.

Appendix 1.8 provides examples for all the statutory filings used in this paper for Metlife's biggest subsidiary (NAIC Code 65978) as of the end of 2019 and Panel C of Table 1.2 provides summary statistics for the main variables that are used in this paper. Panel C1 reports statistics for the firm-year observations for variables in the *Net Income Statement*. The premiums collected for an average firm are in excess of three times the investment earnings,[9] and 1.5 times the market capitalization of life insurers. Panels C2 and C3 provide the statistics for variables in *Exhibit 1: Premiums and Annuity Considerations* and *Analysis of Increases in Reserve*. Both panels indicate that the new customer market is equally important to existing customers in terms of flow.

**Quantities** Finally, I discuss the supply and demand aspects of the profit made from new customers. Assuming that products are homogeneous, the profit can be simplified as the product of profit made from each policy multiplied by the quantity sold:

$$Prem^{New} - Pol^{New} \equiv (P - V)Q,$$

where $P$ denotes the homogeneous price of insurance products, $V$ is the market cost of the policies, and $Q$ is the quantity sold. Due to data limitations, I can't make any quantitative statement concerning the prices of insurance products. Instead, I use two proxies for the quantity of insurance sold during the period. The first is the additional face value of the products sold. This represents the promised amount of payouts for policyholders, and reflects the equilibrium demand for insurance. The second is the additional number of policies sold. The data is collected from *Exhibit of Life-Amount of Insurance*.

Appendix 1.8 provides examples for the statutory filings introduced in this section for Metlife's biggest subsidiary (NAIC Code 65978) as of the end of 2019. Panel C4 of Table 1.2

[9]This is the investment earnings reported in the net income statement, and is not used in the main analysis in this paper. It is reported here to reflect the magnitude of investment earnings. The investment return used in the analysis are measured following Section 1.2.1

reports the statistics for variables in *Exhibit of Life-Amount of Insurance*. Life insurers have gigantic face values of outstanding policies that are almost 60 times the market capitalization. The average gross flow for both the face value and quantity is in excess of 10%.

### 1.2.3 Other: Fixed-income Indices and Risk Factors

I use Bloomberg Barclays US total return indices for all the index-related calculations.

I include term structure risk factors introduced by Litterman and Scheinkman [1991]. I denote the corporate high yield index returns as the *credit* factor returns and the treasury index returns as the *level* factor returns. The *slope* factor returns are calculated as the difference between the long-term treasury index returns (i.e., ten years or more to maturity) and the short-term treasury index returns (i.e., under one year maturity) return. The *curvature* factor returns are calculated as two times the treasury index returns subtracted by the sum of the long-term and the short-term treasury returns.

I use the investment grade corporate index, the municipal bond index, the MBS index, and the treasury index with five to seven years of maturity as the benchmark for the respective asset classes. The detailed components of these indices, along with the correlation between the benchmark indices and the risk factors, can be found in Appendix 1.9.5.

## 1.3 Decomposition of Insurers' Market Equity

In this section, I study the variation in insurers' market equity returns and the origins of the variation following the decomposition in Equation 1 where insurers' market equity returns can be decomposed into net financial asset returns and net business asset returns.

### 1.3.1 Time Series Analysis

I first analyze the time series risks for the aggregate insurance sector's market equity and its constituents. Figure 1.2 presents the aggregate returns and the one year rolling CAPM betas for insurers' aggregate market equity, net business assets, and net financial assets. As illustrated in the plot, net business assets drive most of the variation in insurers' market equity in both aggregate time series. In addition, insurers' market equity and net business assets' CAPM betas are higher than 1 most of the time. Alternatively, their net financial assets' CAPM betas are around zero, with no correlation with neither the market equity CAPM betas nor net business assets' CAPM betas outside of the 2008-2009 financial crisis.

A risk factor model provides a convenient way to study the variations in insurers' equity returns. I provide three sets of results for different risk factor model specifications: (1) a single factor model: CAPM, (2) a two factor model including excess market returns and excess credit returns, and (3) a seven factor model including the Fama French three factors (i.e., market, size, and value) and the term structure risk factors *level, slope*, *curvature*, and *credit.* All of the risk factors are constructed as returns to respective tradable indices, and *level* is omitted whenever excess returns are used for both the dependent and independent variables.

Table 1.4 presents the main results. Panel A provides market equity returns' risk loadings. As shown in Columns 1 to 3, market equity returns have a consistent point estimate of significant market betas that exceed 1 across different specifications. In addition, the adjusted $R^2$ for the CAPM specification is 61% indicating that the variation in equity market returns alone can explain over half of the variation in insurers' market equity returns. As shown in Columns 4-6, net business asset returns have a consistent point estimate of significant market betas whose magnitude is close to the market betas for insurer' market equity. Alternatively, as shown in Columns 7-9, the magnitude of net financial asset returns' CAPM beta is much smaller and the they do not load significantly the equity market returns after controlling for the credit market risk.

Moreover, insurers' market equity essentially has zero or negative credit exposures after controlling for the equity market risk. Not surprisingly, insurers' net financial assets load significantly on the credit market as they are major levered fixed-income investors. The loading on credit risk is significant and exceeds 1 with unchanged estimates across different specifications. However, the credit risk exposures are completely hedged by the negative credit loadings of net business asset returns.

### 1.3.2 Cross-sectional Analysis

In this section, I analyze the cross-sectional risks for insurance companies' market equities and their constituents. I provide two sets of results for different risk factor model specifications: (1) a single factor model: CAPM and (2) a single factor model including the excess credit returns.

Figure 1.4 provides the cross-sectional results where each dot represents a firm. The left plot reports CAPM betas for the net business assets and market equities on the y-axis and for net financial assets on the x-axis. There is little cross-sectional variation in net financial assets' CAPM betas, while there is quite a lot of cross-sectional variation in market equity CAPM betas which is essentially all driven by the variation in net business assets' CAPM betas. In addition, firms whose net financial assets' CAPM betas are high do not have systemically high mark equity CAPM betas. There is zero cross-sectional correlation between the net financial assets' CAPM betas and market equity CAPM betas; the point estimate for the correlation is 0.09 (t-statistic 0.42).

The right plot of Figure 1.4 reports the single factor credit betas for the net business assets and market equities on the y-axis and for net financial assets on the x-axis. Similarly, the variation in market equity credit betas is essentially all driven by the variation in net business assets' credit betas. The point estimate for the cross-sectional correlation between net financial assets' credit betas and market equity credit betas is 0.23 (t-statistic 1.08).

### 1.3.3 Additional Robustness Checks

To demonstrate the robustness of the main results reflected in Table 1.4, I present three sets of robustness checks. First, I exclude the financial crisis from the sample period and present the results for the same risk exposure specifications for the aggregate net business assets and the net financial assets. The loadings are presented in Panel A of Table 1.5. During the financial crisis, credit returns and equity market returns highly co-move, while outside of the crisis, they are typically less correlated. Consistent with this intuition, the $R^2$ for the CAPM specification of the net financial assets becomes really small. The results remain unchanged for net business assets.

In the second robustness check, I construct orthogonal risk factors to address the concerns that credit risks are correlated with fixed-income factors and the equity market factor, and to understand the magnitude of the additional risk exposure. In particular, in the order of level, slope, curvature, credit, market, SMB, and HML, I sequentially orthogonalize the risk factors. For example, $CRED^e$ is defined as the component of the credit factor that cannot be explained by level, slope, and curvature and $MKT^e$ is the component of the market factor that cannot be explained by level, slope, curvature, and credit. Using the same three sets of specifications, the risk exposure for orthogonal risk factors are provided in Panel B of Table 1.5. The results remain unchanged for the net financial assets. Alternatively, net business assets now load on the orthogonal credit factor. The additional equity market risks that are orthogonal to credit and other fixed-income factors remain puzzling.

Finally, I present the annual regression results using all of the reported assets in life insurers' statutory filings in Panel C of Table 1.5. The risk exposure properties remain unchanged. The magnitude for net financial assets' risk loadings is slightly higher because the scaler $(A^I/E)$ now includes the value of all of the financial investments in the numerator.

## 1.4 Business Operations

In this section, I study how much of the net business assets is created through business operations. The value of business operations can be viewed as the net present value of future operation cash flows. Thus, the theoretical definition of the net business asset returns that is derived from business operations is the change in expectations of the value of business operations:

$$\frac{E_{t-1}^{Bus}}{E_{t-1}} R_t^{Bus} = (\mathbb{E}_t - \mathbb{E}_{t-1})\left(\sum_{j=0}^{\infty} \frac{CF_{t+j}^{Bus}/E_{t+j}}{1 + R_{t \to t+j}}\right), \tag{7}$$

where $R_{t \to t+j}$ is the cumulative cost of capital for the time period from $t$ to $t + j$.

### 1.4.1 Business Operation Cash Flows

To understand the impact business operation cash flows have on net business assets, I first study the properties of the business operation cash flow shocks.

**Time Series Analysis** Table 1.6 provides the risk loadings for insurers' aggregate business operation cash flows. Columns 1-3 report the risk loadings for the level and Columns 4-6 report the risk loadings for the estimated AR(1) shocks. In both cases, business operation cash flows load significantly on the equity market risk. The magnitude of the risk loading on equity market suggests that for every 1% increase in equity market returns, insurers' operation cash flows increase by 0.2%. This magnitude is similar to the average risk loading for the industries whose net income has cyclicality.[10]

I then show the risk loadings for the decomposition of insurers' business operation cash flows. As presented in Equation 6, business operation cash flows can be divided into profit from new customers and profit from existing customers. Table 1.8 provides the risk loadings for the breakdown of the business operation cash flows. Columns 1-3 present the risk loadings of profit from new customers, net of commissions paid to insurance agents. Columns 4-6 report the risk loadings for profit from existing customers. Sales of new insurance products expose insurance companies positively to the equity market risk and negatively to the credit risk after controlling for the market risk. Alternatively, the net profit insurance companies make from existing customers is not exposed to any market related risk factors. The ex-

[10] I calculate the aggregate AR (1) shocks for each industry at the 3-digit SIC level and run the 7 factor specification. The average risk loading for the industries with significant loadings on the equity market is 0.24 (0.12 for the entire sample).

planatory power of these market risk factors is also small with negative adjusted $R^2$. This is not surprising as profits made from existing customers are more likely to be exposed to insurance specific risks (e.g., model misspecification).

To be able to disentangle whether the cyclicality of profits made through sales of insurance products is a result of supply or demand shocks, I study the risk exposures of the quantities of insurance products sold in the aggregate time series. Table 1.7 presents the risk loadings for the quantities of insurance products sold. Panel A reports the results for life insurance products and Panel B reports the results for annuities. In Panel A, the dependent variable is set to be the face value of new life insurance sold as a ratio of life insurance in force at the end of the last period ($\nabla^+$ Face Value, Columns 1-3) and the number of new life insurance policies sold as a ratio of the total number of life insurance policies at the end of the last period ($\nabla^+$ Number, Columns 4-6). These quantity measures are counter-cyclical or acyclical. This is suggestive evidence of supply shocks (or simultaneous demand and supply shocks). Assume that insurance products are homogeneous and one unit of product promises one dollar payout in the future. The profit insurers make from the sales of products is $(P - V)Q$, where $V$ is the fair present value of one unit of product, $P$ is the price insurers charge for one unit of product, and $Q$ is the number of units sold. $V$ is exposed to risk-free term structure risks and is assumed to be acyclical. Empirically, $Q$ can be interpreted as the face value of new insurance sold. Consider insurance companies as competitive monopolies facing a downward sloping demand curve such that $Q = q(P)$ and $\partial q/\partial P < 0$. The fact that profits are pro-cyclical while $Q$ is counter-cyclical in equilibrium implies that there are supply shocks (or simultaneous demand and supply shocks). It is natural to think of a pro-cyclical demand shock that shifts the demand curve. When there is a negative (positive) demand shock, the profit maximizing quantity will be lower (higher). The fact that $Q$ is counter-cyclical is suggestive evidence of a simultaneous supply shock.

Interestingly, the equilibrium quantities of life insurance policies and annuity policies exhibit different patterns. In particular, sales of life insurance policies change at the intensive margin while sales of annuity policies change at the extensive margin. The face value of new life insurance policies sold is counter-cyclical while the number of new life insurance policies sold is acyclical. This suggests that the number of customers seeking for life insurance does not change with economic conditions. However, for each new policy, customers insure for less face value in booms. On the other hand, consistent with the literature (e.g., Previtero [2014]), annuity sales are strongly counter-cycle, especially for policies that are related to defined benefit plans.

**Cross-Sectional Analysis** Insurers actively offload the risks from their investment portfolios to new customers, and use the sales of new products to hedge insurance specific risks caused by outstanding insurance policies. Table 1.9 provides the results for the following panel regression:

$$\frac{Y_{i,t}}{E_{i,t-1}} = \alpha + \beta_0 \frac{CF^{Old}_{i,t}}{E_{i,t-1}} + \beta_1 \frac{A^I_{i,t-1}}{E_{i,t-1}} R^I_{i,t} + \gamma_i + \eta_t + \epsilon_{i,t}, \tag{8}$$

where the dependent variable $Y$ is set to the profit from new customers ($CF^{New}$, Columns 1-3) and minus the operation costs ($-C$, Columns 4-6). The negative coefficients suggest that the net profit made from new customers is used to hedge investment risk and risks introduced by the outstanding products.[11] Part of the investment risk is also offloaded to agents through commission payments. One possible interpretation of this hedging behavior is that insurers use business operations to smooth out their book equity. This evidence is consistent with Adrian, Boyarchenko, and Shin [2015] who argues that banks actively smooth book equity by adjusting payouts to achieve a desired trajectory of book equity.

[11] The implicit assumption for this causality interpretation is that investment return shocks are exogenous. One may argue that insurers invest the profit they make from the business operation market into the financial market. Since they are the largest corporate bond holders, this may cause price movement in corporate bonds. If this is the case, the effect should not be present in the cross-section. The panel regression with year fixed effects is able to address this concern.

### 1.4.2 Variance Decomposition of the Net Business Assets

As demonstrated in previous sections, insurers actively manage their business operations and these cash flows are strongly procyclical. In this section, I study how important business operation cash flows are to understanding variation in net business asset returns.

**Decomposing the Net Business Asset Returns** I adopt an accounting-based formula similar to Vuolteenaho [2002] to understand the relative importance of business operation cash flows and discount rates.[12]

Three main assumptions are made in order to derive the net financial asset version of the approximate present-value model. First, net financial assets ($E^{Fin}$), dividend to stockholders ($Div$), and market equity ($E$) are assumed to be strictly positive. Second, the difference between the log net financial assets ($f$) and the log market equity ($m$) and the difference between the log dividend ($d$) and the log net financial assets are assumed to be stationary. Third, the earning, dividend to stockholders, and the net financial assets satisfy the clean-surplus identity:

$$E_t^{Fin} = E_{t-1}^{Fin}(1 + R_t^{Fin}) + CF_t^{Bus} - Div_t, \tag{9}$$

- the net financial assets this year equal the net financial assets last year, plus the financial earning and the net business asset dividend paid to the net financial asset account, less the dividend paid to stockholders. I denote the total income return by $R_t = (E_{t-1}^{Fin} R_t^{Fin} + CF_t^{Bus})/E_{t-1}^{Fin}$ and the log total income return by $e_t = \log(1 + R_t)$. Similarly, I denote the log of the *unscaled* net financial asset return as $e_t^{Fin} = \log(1 + R_t^{Fin})$. For notation ease, the *log business-cash-flow return* is defined as the difference between the log total income return and the log of the *unscaled* net financial asset return ($e_t^{Bus} = e_t - e_t^{Fin}$). Finally, the

[12] Campbell [1991] uses the dividend-growth model to decompose aggregate stock return, and Vuolteenaho [2002] uses an accounting-based formula having ROE (earnings over book equity) as the basic cash-flow fundamental instead of dividend growth. Whether one chooses to think about infinite-horizon cash-flow fundamentals in terms of dividend growth of ROE is a matter of taste.

*log adjusted net business asset return* (henceforth *log adjusted business return*) is defined as the difference between the log equity return and the log of the unscaled net financial asset return ($r_t - e_t^{Fin}$).[13] Following Vuolteenaho [1999], I can decompose the unexpected-adjusted -business return as:

$$(r_t - e_t^{Fin}) - \mathbb{E}_{t-1}(r_t - e_t^{Fin}) = \Delta\mathbb{E}_t \sum_{j=0}^{\infty} \rho^j e_{t+j}^{Bus} - \Delta\mathbb{E}_t \sum_{j=1}^{\infty} \rho^j (r_{t+j} - e_{t+j}^{Fin}) + \epsilon_t. \tag{10}$$

where $\Delta\mathbb{E}_t$ denotes the change in expectations from $t-1$ to $t$ and $\epsilon_t$ is the estimation error. As long as some dividends are paid to the stockholders, the discount coefficient satisfies $\rho < 1$. The optimal value for $\rho$ in my sample is 0.96. The details of the derivation and the choice of $\rho$ are introduced in Appendix 1.10.1. Denote the *business-cash-flow news* ($N_{cf,t}$) and *expected-adjusted-business-return news* ($N_{r,t}$) as follows:

$$N_{cf,t} \equiv \Delta\mathbb{E}_t \sum_{j=0}^{\infty} \rho^j (e_{t+j} - e_{t+j}^{Fin}) + \epsilon_t;\ N_{r,t} \equiv \Delta\mathbb{E}_t \sum_{j=1}^{\infty} \rho^j (r_{t+j} - e_{t+j}^{Fin}). \tag{11}$$

The variance of shocks to the log adjusted-business returns can then be decomposed into three components following Equation 10 and 11:

$$\text{var}\Big((r_{t+j} - e_{t+j}^{Fin}) - \mathbb{E}_{t-1}(r_{t+j} - e_{t+j}^{Fin})\Big) = \text{var}(N_{cf,t}) + \text{var}(N_{r,t}) - 2\text{cov}(N_{r,t}, N_{cf,t}) \tag{12}$$

**Results and Discussion** A vector autoregressive model provides a convenient way to implement the return decomposition. For the panel VAR, let $z_{i,t}$ be a vector of firm specific state variables describing firm $i$ at time $t$. An individual firms' state vector is assumed to follow a VAR (1):

$$z_{i,t} = \Gamma z_{i,t-1} + \omega_{i,t}.^{14} \tag{13}$$

[13] The adjustment made here is $\log(1 + E_{t-1}^{Bus} R_t^{Bus}/E_t) \approx r_t - \log(1 + E_{t-1}^{Fin} R_t^{Fin}/E_t) \approx r_t - e_t^{Fin} - \theta_t$.

[14] The assumption that the VAR is first-order is not restrictive, as a higher-order VAR can always be stacked into first-order (companion) form in the manner discussed by Campbell and Shiller [1988]. The matrix $\Gamma$ is known as the companion matrix of the VAR.

The VAR coefficient matrix $\Gamma$ is assumed to be constant, both over time and across firms. The error term $\omega_{i,t}$ is assumed to have a covariance matrix $\Sigma$, which is independent of everything known at $t$. I set the first element of $z_{i,t}$ to be the log adjusted-business return and Define $e1' \equiv [1\ 0\ ...\ 0]$ and

$$\lambda' \equiv e1'\rho\Gamma(I - \rho\Gamma)^{-1},$$

the expected-adjusted-business-return news can then be conveniently expressed as $\lambda'\omega_{i,t}$ and the business-cash-flow-return news as $(e1'+\lambda')\omega_{i,t}$. The news variance matrix on the business-cash-flow shocks is:

$$\begin{aligned}
\text{var}(N_r) &= \lambda'\Sigma\lambda \\
\text{var}(N_{cf}) &= (e1' + \lambda')\Sigma(e1 + \lambda).
\end{aligned}$$

I study 3 specifications.[15] The first specification follows the aforementioned derivation and uses the market-adjusted (cross-sectional demeaned) log adjusted business return ($r - e^{Fin}$), the log net financial assets to market equity ratio ($\theta = f_t - m_t$, henceforth log financial-to-market), and the log business-cash-flow return ($e - e^{Fin}$) as the state variables. The model implied standard deviation for the expected-adjusted-business-return news is 12%, while the standard deviation for the business-cash-flow-return news is 20%. The variance of the business-cash-flow news explains 74% of the total variation of the unexpected shocks the adjusted-business returns. The magnitude of the explanatory power of the business-cash-flow news is similar to Vuolteenaho [2002]'s estimate for the entire market portfolio. This indicates that the business-cash-flow news is as important for insurers as it is for the rest of

[15]The data used for the VAR estimation is described in Appendix 1.10.1 and all the parameter estimates are provided in Appendix 1.10.2.

the market portfolio.[16]

The second specification decomposes shocks to *total equity return* into *total cash-flow news* and *total expected-return news.* This specification uses market-adjusted (cross-sectional demeaned) log equity returns ($r$), the log financial-to-market ratio ($\theta$), and the log total income returns ($e$) as the state variables. The total expected-return news standard deviation implied by this specification is 5% while the total cash-flow news standard deviation is 15%. The variance of the total cash-flow news explains 90% of the variance of the total unexpected equity shocks. The excess explanatory power of total cash-flow news over business cash-flow news comes from financial cash-flow news. Comparing to the explanatory power of the business-cash-flow news, financial cash-flow news is only able to explain 16% more of the total unexpected shocks.

The third VAR specification uses same state variables as the first specification, except that the state variables are demeaned within the sample across firms and years. This allows me to capture the time varying perspective of the business-cash-flow shocks.[17] I compare insurers' value-weighted business-cash-flow shocks to the market portfolio's value weighted cash-flow shocks and the two aggregate time series are shown in Figure 1.6 from 2001 to 2017.[18] The correlation is 0.64 with a t-stat of 3.275. The fact that these two time series are so correlated provides an explanation to the high equity CAPM betas.

To demonstrate the robustness of the fact that insurers' business-cash-flow shocks are correlated with market cash-flow shocks, I present three sets of robustness checks. I first

[16]A direct way of obtaining the business-cash-flow news is directly calculate the change in the discounted sum of business-cash-flow returns. Define $e3' \equiv [0\ 0\ ...\ 1]$, the direct business-cash-flow news ($N_{cf}^{D}$) is thus $e3'(I-\rho\Gamma)^{-1}\omega_{i,t}$ and the variance is $(e3'(I-\rho\Gamma)^{-1})'\Sigma(e3'(I-\rho\Gamma)^{-1})$. The difference between the direct measure and indirect measure introduced in the text is the estimation error $\epsilon_t$. The variance of the indirect business-cash-flow news is much smaller than the variance of the direct business-cash-flow news. This indicates that the measurement error is negatively correlated with business-cash-flow shocks and suggests that attributing the error term to cash-flow news provides a conservative estimate of the importance of the business-cash-flow shocks.

[17]The estimated constants for the VAR are not necessarily zero anymore, I estimate the model including the intercepts. Vuolteenaho [2002] also controls for the macro conditions by including the median of the state variables for each year as addition state variables. This specification yields similar results.

[18]For the cash-flow shocks to the market, I decompose equity returns for firms in the market portfolio into cash-flow news and expected-return news using log equity return, log book to market ratio, and log ROE as state variables, de-meaned within the 3 digit SIC code.

confirm that insurers' aggregate business-cash-flow shocks are correlated with the aggregate cash-flow shocks for firms in the market portfolio in an aggregate VAR setup, having the aggregate log business-cash-flow return, the aggregate log financial-to-market ratio, and the log business-cash-flow return as state variables. I then present the same results for a long aggregate VAR set up, having the aggregate log total equity return, the aggregate log financial-to-market ratio, th aggregate log financial return and the log business-cash-flow return as state variables. Details are provided in Appendix 1.10.3. I then confirm the evidence in a finite horizon setup to address the concern that the VAR model assumes an infinite horizon. In particular, I compare insurers' long term cumulative business-cash-flow returns and the market portfolio's long term cumulative returns on equity (ROE) and show that these two series are highly correlated. The fact is robust to using different length of horizons. Details are presented in Appendix 1.11.

### 1.4.3 Direct Measure of the Net Business Asset Returns

In this section, I impose some structures on the aggregate business operation cash flows and estimate the value of growth opportunities associate with business operations directly. I assume that the aggregate business operation cash flows follow an AR(1) as follows:

$$\frac{CF_{t+1}^{Bus}}{E_t} = \rho \frac{CF_t^{Bus}}{E_{t-1}} + \delta_{t+1}^X,$$

where $\rho$ is assumed to be constant over time and $\delta^X$ is shock to business operation cash flow. Figure 1.7 presents the ACF test for $CF^{Bus}/E$ and confirms the one period persistence.

The growth rate of insurers' market equity and the cost of capital are assumed to be as follows:

$$\frac{E_{t+1}}{E_t} = \delta_{t+1}^G \ ; \ R_{t \to t+1} = \delta_{t+1}^R,$$

where both shocks have a positive mean. The shocks to business operation cash flows, the growth rates of market equity, and the shocks to cost of capital are all correlated with each other (the correlation matrix is not modeled explicitly).

Rewrite the theoretical definition of the value of growth opportunities associated with business operations in Equation 7 to reflect the effects from different type of shocks as follows:

$$\frac{E_t^{Bus} + CF_t^{Bus}}{E_{t-1}} = \mathbb{E}_t(\sum_{j=0}^{\infty} \frac{CF_{t+j}^{Bus}}{E_{t+j-1}} \frac{E_{t+j-1}}{E_{t-1}} \frac{1}{R_{t \to t+j}}). \tag{14}$$

I assume that the joint distribution of the random shocks is common knowledge and not time varying. The change of Equation 14 from $t-1$ to $t$ then yields an expression for the net business asset return:

$$\frac{E_{t-1}^{Bus}}{E_{t-1}} R_t^{Bus} = \mu \sigma_t^X, \tag{15}$$

where $\mu$ is a constant determined by the moments of the joint distribution of the random shocks. Detailed derivation is provided in Appendix 1.12. This model implies that the shocks to the business operation cash flows are the key that drives the net business asset returns. Figure 1.8 plots the shocks implied from the AR(1) model for $CF^{Bus}/E$ and the net business asset returns. These two aggregate time series are positively correlated with a point estimate of 0.38 (t-stat 3.29). The significant correlation indicates that growth opportunities associated with business operations are indeed part of the net business assets.

## 1.5 Other Sources of the Net Business Assets

I now turn to other potential sources of the value of net business assets and provide arguments on why these are not the key source to explain the high CAPM beta in insurers' market equity.

### 1.5.1 Asset Management Value

In this section, I demonstrate that insurers are passive fixed-income investors and don't exhibit substantial asset management value from trading. This is consistent with the findings of Begenau and Stafford [2019] who argue that banks' don't have an edge in asset management. I overcome the measurement challenges in Begenau and Stafford [2019] by using CUSIP level asset holding data for insurers, and confirm that insurers also don't have an edge in asset management. In fact, insurers' asset portfolios behave as if they are a combination of the fixed-income indices.

**Within Asset Classes** I begin by demonstrating that insurers track benchmarks closely for each asset class. I denote the index return for asset class $k$ at time $t$ as $IND_t^k$, and insurers' value-weighted return for asset class $k$ as $R_t^k$. I derive the coefficient estimates for the following regression for each $k$:

$$R_t^k - R_t^f = \alpha^k + \beta^k(IND_t^k - R_t^f) + \epsilon_t^k. \tag{16}$$

If the coefficients for asset class $k$ satisfy simultaneously that $\alpha^k$ is close to zero, $\beta^k$ is close to one, and the R square is close to one, I conclude that insurers mimic the index returns well for asset class $k$. Table 1.10 presents the main results for the coefficient estimates.

I present the results for the aggregate time series in Columns 1-3. In aggregate, firms track the indices closely for all fixed-income asset classes with betas close to one and reasonably high R squares. This is especially true for corporate bonds that represent the largest portion of the insurers' holdings. R squares for municipal bonds and MBS are not as high. One possible reason is that it is difficult to track the especially illiquid assets included in these indices. Columns 4-9 of Table 1.10 present the summary statistics for the cross-sectional results where I run the regression in Equation 16 for each asset class for each firm separately. Column 4 provides the average of the statistically significant alphas, while Column 5 reports the number of firms that have significant alphas. There is only a small fraction of firms have significant alphas and the magnitude of significant alphas is small. Column 6 presents the average of betas, while Column 7 provides the cross-sectional standard deviation of betas. On average, betas are close to one for each asset class and there is little deviation. Column 8 provides the average R square, while Column 9 reports the cross-sectional standard deviation of R squares.

Appendix 1.13 discusses the investment behavior for sub-periods before and after the financial crisis separately. I show that insurers track indices closer after the financial crisis and thus yields lower asset management value. However as shown in Figure 1.2, insurers have higher CAPM betas after the financial crisis. This contradictory evidence suggests that asset management value is not likely to explain the high variation in insurers' market equities.

**Across Asset Classes** I consider 2 types of passive investors. I consider the case in which asset weights are kept constant over time across asset classes. I also consider the case in which no rebalancing across asset classes occurs. I find suggestive evidence that insurers' strategy for asset class weights is in between these two alternatives. For the first case, I check the time series of the level of asset class weights. If the weights stay unchanged, it suggests insurers always rebalance to a fixed asset class weight. In the top plot of Figure 1.5, I plot the level of weights for all tradable asset classes. They are stable overtime and the largest movement is during the financial crisis when insurers shift investments in corporate bonds to cash. This shift is small in magnitude and will not introduce any additional risks.

In the second case, I study the active rebalancing. I denote $\Delta\omega_{i,t}^k$ as firm $i$'s active weight change for asset class $k$ at time $t$:

$$\Delta\omega_{i,t}^k = \omega_{i,t}^k - \omega_{i,t-1}^k R_{i,t}^k / \overline{R_{i,t}^k}; \tag{17}$$

where the first term is the asset class weight at the end of time $t$ and the second term is the passive asset class weight after the realization of the current period returns. The asset classes that have a higher realized returns (i.e., asset return $R^k_{i,t}$ is higher than the average return across asset classes $\overline{R^k_{i,t}}$) will have greater passive weights in the next period. As illustrated in the bottom plot in Figure 1.5, active weight changes for different asset classes are close to zero with the 25th and 75th percentile being $-0.5\%$ and $0.5\%$. The largest movement is again during the financial crisis when insurers shift investments in corporate bonds to cash.

### 1.5.2 Asset Insulation

Life insurers may derive net business asset value through asset insulation. Chodorow-Reich, Ghent, and Haddad [2020] present a theory of asset insulation as an explanation to the low correlation between life insurers' equity returns and net financial asset returns. They propose a mispring model where two valuations for the same asset coexist: the price observed on the market and the value of the asset to a long-term investor. The price observed on the public market is a mispriced value of the long-term value which is defined as the expected discounted cash flow value of an asset. They argue that in normal times when insurance companies are far from liquidation, their market equity valuation is completely driven by shocks to the long-term asset value. The shocks specific to assets' market value that do that affect their long-term value do not get passed through to insurers' equity valuation. The average of these two effects yields a low correlation between insurers' equity returns and net financial asset returns. Although the asset insulation is a compelling theory in terms of understanding the low pass-through, it is not able to justify insurers' high market equity betas. First, asset insulation implies that only part of the risks of net financial assets get passed through to equities and the process will not introduce new type of risks. Second, the value of asset insulation is determined by the relative variances of respective shocks to the long-term asset value and other market specific risks. As neither of these risks include the equity market risk, it is not likely that the relative variances are correlated with the equity market.

### 1.5.3 Government Guarantees

Financial institutions may also derive net business asset value from government guarantees of their liabilities (e.g., Atkeson, d′Avernas, Eisfeldt, and Weill [2019], Berndt, Duffie, and Zhu [2019]). These guarantees include explicit backing of liabilities, such as deposit insurance for commercial banks and state guaranty funds for life insurers, and implicit expectation of bailouts in extreme market conditions. Because of the presence of government guarantees, a dollar lost on assets yields less than a dollar lost in equity and this is consistent with the results that insurers' market equity has a lower credit beta than their net financial assets. However, the value of government guarantees increases during the time period when insurers are closer to liquidation and is likely to be countercyclical. In addition, the value of government guarantees is homogeneous in the cross section. The fact that there is a large cross-sectional variation in insurers' market equity betas makes the variation in the value of government guarantees less likely to be an explanation.

### 1.5.4 Others

Another possible source of the net business asset value is the value created through the regulatory arbitrage abilities which largely depends on the shadow price of binding regulatory constraints. Similar to the value of government guarantees, the shadow price of the binding regulatory constraints is likely to be countercyclical. Finally, the value of net business assets can also come from the time varying brand value of life insurers. Large and systemically important firms exhibit higher brand value in the downturns which further leads to a higher aggregate brand value in the downturns.

## 1.6 Implications

In this section, I document the macroeconomics importance of understanding financial firms' net business asset returns.

### 1.6.1 External Validity

All the main results in this paper using life insurers as a laboratory can be applied to other systemically important financial firms especially for banks. Despite of having different forms of business operations, banks share a lot of similarities with life insurers. First, they are both fixed-income investors with fairly high leverage and they hold these financial securities as principal holders. Second, they both have simply structured liabilities that are relatively safe and are closely related to their business operations. Banks' liabilities are mostly in the form of deposits while life insurers' liabilities are mostly in the form of insurance products. The properties of these two forms of liabilities can be easily inferred from the characteristics of banks' or insurers' customers.

The biggest limitation of studying banks is that banks' financial security holdings are filed at the aggregate level for each asset class. To empirically measure banks' net financial assets, literature has been using fixed-income index returns for each asset class, assuming that banks track indices closely within asset classes (e.g., Begenau and Stafford [2019]). Using detailed CUSIP level holding data, I am able to confirm this investment strategy for insurers as indicated in Section 1.5.1. In addition, I am also able to confirm that insurers' book equity tracks the variation of their net financial assets well.[19] Figure 1.9 presents insurers' aggregate net financial asset returns measured using detailed portfolio holding data and net financial assets returns measured using book equity. These two measures have a significant correlation of 0.7 (t-stat: 6.6), confirming the fact that financial firms' book equity is a good proxy for their net financial assets. I thus use banks' book equity to proxy for their net financial assets to test for external validity. Figure 1.10 presents the aggregate book equity and market equity for insurers and banks over the time period of 2002 to 2018. For both insurers and banks, their book equity is only able to explain very little variation in the level and changes of market equity. Comparing to insurers, banks' book equity exhibits even less

[19]Since GAAP requires financial firms to have their assets marked-to-market, their book equity will reflect variation in their financial asset holdings.

explanatory power towards the variation in their market equity. This suggests that using life insurance companies as a laboratory is a conservative way to study the importance of net business assets to financial firms' valuation.

### 1.6.2 Implication to Financial Soundness and Regulations

I demonstrate that insurers' net business asset returns, rather than their net financial asset returns, serve as a good financial soundness measure.

Two commonly used financial soundness measures that reflect the actual financial market risks are shocks to intermediaries' capital ratio (e.g. He, Kelly, and Manela [2017], henceforth HKM), and financial firms' CDS spread. Insurers' net business asset returns are highly correlated with both of the measures, indicating that the variation in business assets is able to speak to financial soundness. The correlation between the net business asset returns and HKM is significantly positive with a point estimate of 0.45 (t-stat 4.2), and the correlation between the net business asset returns and the financial firms' value-weighted 5-year CDS spreads is significantly negative with a point estimate of $-0.32$ (t-stat 2.69).

On the other hand, the financial soundness indicators that measure net financial asset returns have 0 correlation with neither HKM nor financial firms' CDS spreads. IMF introduces a set of financial soundness indicators after the 2008 financial crisis as a precaution for future financial downturns. The two main financial soundness indicators introduced are *Regulatory Tier 1 Capital as a Percent of Risk-Weighted Assets* and *Liquid Assets as a Percent of Short-Term Liabilities*, both measure the riskiness of the financial assets that are held by financial firms. IMF shows that these measures are highly correlated with *the ratio between regulatory capital and risk-weighted assets* which is the main indicator used by the regulators to measure financial firms' level of riskiness. In recent years, financial firms are viewed as very safe as indicated by the regulatory measurement and due to a preponderance of policies regulating their investment portfolios. However, the fact that net business asset returns are highly volatile suggests that a great deal of risk is derived from the nonfinancial component of financial firms (i.e., business operations).

Current regulations are largely imposed on financial firms' net financial assets. These regulations are able to ensure that financial firms do not go into insolvency because of the excess risks they undertake with their investment portfolios. In addition, proper monitoring of net financial assets also makes sure that financial firms' assets are sufficient to pay off outstanding liabilities in the case of default. However, the risks derived from net business assets are overlooked by existing regulations and the high volatility embedded in financial firms' net business assets may lead to insolvency. Given the importance of financial firms as systematic players in the economy, their failures have consequences even when they are able to pay off their liabilities. From the macro perspective, financial firms may have to fire sale their assets in the case of default, which is likely to crash the market given the large size of the financial portfolio they hold. From the micro perspective, reallocation of financial resources can be costly and may lead to adverse selection problem. Thus, it is crucial for the regulators to be aware of the flexibility financial firms have with their business operations.

### 1.6.3 Implication to Intermediary Asset Pricing

The empirical literature on intermediary asset pricing argues that intermediaries' marginal value of wealth provides an informative stochastic discount factor (SDF) that determines asset prices because they are the marginal investors in the financial market. This is motivated by the theoretical models considering intermediary net worth as a simple function of the performance of their net financial assets (e.g., He and Krishnamurthy [2013]). For example, He, Kelly, and Manela [2017] demonstrate that the change in net worth of broker-dealers is a powerful pricing factor for the cross section and time series of returns for a wide range of asset classes. They argue that this is because broker-dealers are marginal investors in all markets. The implicit assumption with this argument is that the pricing power is derived from intermediaries' net financial asset returns. I provide a new view on intermediary asset pricing that the pricing power in different markets can come from different types of returns.

In particular, I use insurers to demonstrate that intermediaries are also able to price assets that they barely hold through net business asset returns.

Following He and Krishnamurthy [2013], for any asset $i$ with instantaneous return $dR_t^i$, the first-order condition of the intermediary implies:

$$\mathbb{E}_t(dR_t^i) - R_t^f dt = \mathrm{Cov}_t(\frac{dw_t}{w_t}, dR_t^i),$$

where $dw_t/w_t$ is the marginal wealth of the intermediary and is used as the stochastic discount factor (SDF) to price assets in empirical literature on intermediary asset pricing (e.g., Adrian, Etula, and Muir [2014] and He, Kelly, and Manela [2017]). Denote the instantaneous net business asset return as $dR^{Bus}$, the instantaneous financial asset return as $dR^{Fin}$, and the financial-to-market ratio as $\alpha = E^{Fin}/E$, intermediary's marginal wealth can then be expressed as:

$$\frac{dw_t}{w_t} = \alpha dR_t^{Fin} + (1-\alpha) dR_t^{Bus}.$$

This further implies

$$\mathbb{E}_t(dR_t^i) - R_t^f dt = \mathrm{Cov}_t\Big(\alpha dR_t^{Fin}, dR_t^i\Big) + \mathrm{Cov}_t\Big((1-\alpha) dR_t^{Bus}, dR_t^i\Big) \tag{18}$$

Intermediary asset pricing literature focuses on the first term on the right hand side of Equation 18: the covariance between intermediaries' net financial asset returns and test asset returns. They argue that intermediaries are able to price assets in the markets in which they are marginal essentially because asset $i$ is in the financial portfolios that intermediaries hold. In the case of life insurance companies, as they are the largest corporate bond holders and likely to be the marginal investor, their net financial asset returns should be able to price corporate bonds in the cross section and time series. On the other hand, the second term on the right hand side of Equation 18: the covariance between intermediaries' net business asset returns and test asset returns, as argued in this paper, may not be zero even for assets that are not held by the intermediaries. In the case of life insurance companies, although they do not invest much in the equity market, the fact that their net business asset returns are highly correlated with the equity market returns indicates their strong pricing power in the equity market.

Table 1.11 provides the pricing results. In particular, for each test asset portfolio $i$, I estimate betas from time series regressions of portfolio excess return $R_t^i - R_t^f$ on the pricing factors: net business asset returns $E^{Bus}R^{Bus}/E$, the HKM factor, and the excess market returns. I run the pricing tests for each of the pricing factors separately and also in a horse race setup. In both a shorter sample period during which I can measure life insurers' net business asset returns precisely and a longer sample period where I use the differences between changes in market equity and changes in book equity as a proxy for net business asset returns, the aggregate net business asset returns are able to price equities better than HKM. Meanwhile, as predicted by the model, net business asset returns exhibit little pricing power in the bond market. My results suggest that the explanatory power in HKM for different asset classes may come from different sources of intermediaries' market equity. In addition, my results suggest a missing mechanism in the exiting theoretical framework of intermediary asset pricing considering their net business asset returns.

## 1.7 Conclusion

I have proposed a new view on financial intermediaries' market valuation where most of the variation is driven by the their volatile net business assets. This paper is motivated by the fact that the variation in financial firms' market equity can scarcely be explained by the variation in net financial assets while the variation of net business assets is able to explain 97% of the variation in financial firms' market equity. I use life insurance companies as a laboratory and find that the net business assets, valued as the growth opportunities of their business operations, drive most of the variation in their market equity.

Life insurers are levered fixed-income holders and their asset returns load heavily on the credit risk. Life insurers' policy liabilities are a stream of risk-less long term payments and are primarily exposed to the risks associated with the risk-free term structure. Their market equity, however, do not load much on either the credit risk or term structure risks. Instead, life insurers' market equity has CAPM betas exceeding 1. This implies the there is an additional source of risk that come from the nonfinancial component (net business asset). I determine that 74% of the variation in net business assets is driven by cash-flow shocks to their business operations and that business-cash-flow shocks are highly correlated with market cash-flow shocks, providing an explanation to the high equity CAPM betas.

My study points out that the nonfinancial value of financial firms drives most of the variation in their valuation and my study is a first step in pointing out that financial firms' business operations are just as risky as the business operations for other industries. I see the research on quantitatively disentangle the different sources of net business assets important. Moreover, I view understanding the source of intermediary pricing power as a fruitful area for further research. Finally, during the recent episode of the COVID-19, life insurers' market equities are shocked much more than the value-weighted equity market portfolio and exhibit slower recovery. I regard using COVID as a health crisis shock to study life insurers' equity stock performance as a promising area of future work.

## 1.8 Appendix: Examples of Statutory Filings

This section provides examples for *Net Income Statement* (Table 1.12), *Exhibit 1: Premiums and Annuity Considerations* (Table 1.13), *Analysis of Increases in Reserve* (Table 1.14), *Exhibit of Life-Amount of Insurance* (Table 1.15) for Metlife's biggest subsidiary (NAIC Code 65978), as of the end of 2019.

## 1.9 Appendix: Data

### 1.9.1 Sample

The set of insurers (tickers) in my sample includes: Aflac Inc.(AFL), American Equity Investment (AEL), American General Corp (AGC.1), American National Insurance (ANAT), Athene Holding Ltd (ATH), Brighthouse Financial (BHF), Cigna Corp (CI), Citizens Financial (CFIN), Citizens Inc (CIA), CNO Financial Group Inc (CNO), Cotton States Life Insurance (CSLI), Delphi Financial Group (DFG), FBL Financial Group (FFG), Fidelity & Guaranty Life (FGL), Genworth Financial Inc (GNW), Great American Financial Resources (GFR), Hancock John Financial Services (JHF), KMG America Corp (KMA), Liberty Financial (L.3), Lincoln National Corp (LNC), Metlife (MET), National Western Life (NWLI), National Financial Services (NFS), Primerica (PRI), Principal Financial Group (PFG), Protective Life (PL), Prudential Financial Inc (PRU), Security National Financial (SNFCA), Southern Security Life (SSLI), Symetra Financial Corp (SYA), Torchmark Corp (TMK), Unum Group (UNM), UTG Inc (UTGN), Voya Financial (VOYA). In the cross-sectional analysis, I restrict the firms in the sample to have at least 10 years of observation for annual frequency analysis (19 firms), and at least 5 years of observation for quarterly frequency analysis (31 firms).

### 1.9.2 Textual Analysis and Data Cleaning

In statutory Schedule D filings, insurers report numeric variables for the assets in their portfolio: CUSIP, yield to maturity, coupon rate, coupon frequency, fair value, payments collected, accrued interest, book value, acquired date, acquired cost, par value, and maturity date; as well as string values for asset description, asset type, and issuer type for each asset. I correct for misreporting in the filing by pooling all asset holdings reported by different insurers together. This allows me to adjust for obvious filing mistakes and fill in missing data if there are overlaps between two firms' portfolios (i.e., more than one firm holds the same assets in the same year). Although I focus on analyzing general account investment portfolios, I utilize the separate account holding data in the data cleaning process.

CUSIP is not necessarily unique for fixed-income assets. I use a unique asset identifier: the combination of CUSIP, maturity date and coupon rate to track assets. I rely on the information in the "description" to fill in missing data for the maturity date and coupon rate. There is no unified rule as to what information is to be included in the description. In general, the information that may be included in the description includes issuer's name, the maturity date, and the coupon rate. Whenever this information is available in the description, I scrape them out to fill in the missing values.

For the main analysis, I divide the assets into five big asset classes: corporate bonds, municipal bonds, treasuries, agency-backed MBSs and equities. I first separate stocks and bonds by checking the seventh and eighth digit of the reported CUSIP. Following the CUSIP identifier rule, if both digits are numeric numbers, they represent stocks, and if at least one of them is letter, the CUSIP identifies a bond. For the fixed-income assets, I first identify those that are covered by other data vendors (e.g., TRACE, Bloomberg) that are mostly corporate bonds and treasuries. For the rest, I use information reported for asset types, issuer types, and the description to group assets into the desired categories. The basic rule for grouping is as follows. Assets issued by industrial firms are identified as corporate bonds; assets issued by U.S. states or used to fund public utilities are identified as municipal bonds; assets issued by the U.S. federal government or non-structured products issued by government agencies are identified as treasuries, while structured products issued by government agencies are agency-backed MBS.

I then determine whether an asset is a structured product or not. The reported categories for asset types are different across time, and not exactly consistent across firms. Although the two basic asset types are insurers' obligations and MBS/ABS, the required sub-categories changed in 2004, and insurers began to file in much more detail for asset classes. For example, for MBS, prior to 2004, insurers only report if an asset is single class or multiple class. Post 2004, they also include information to indicate whether an MBS is commercial or residential. Since there is no way to backfill the asset class information in detail prior to 2004, I adopt a wide and general class definition and make sure that they are consistent across time and asset firms. In particular, I study the sub samples for the ones that are reported consistently across firms and years. I then group the key words that are most commonly mentioned in their descriptions in addition to firm name, maturity date, and the interest rate. Some of the keywords may not be mutually exclusive and require manual adjustments.

It is much more complicated to identify issuer's type as insurers don't consistently separate government agencies, the federal government, and U.S. states. This makes it difficult to determine whether an asset is a municipal bond, a treasury bond or agency-backed assets. The methodology I follow is highly dependent on the data available. As issuers' names are usually mentioned in the description, I use a list of government agency names and their abbreviations to identify the misspecified ones for agency-based MBS. I then check the description for county names, city names, and public utilities to determine municipal bonds.

### 1.9.3 Cross-Check for Asset Returns

There are 284,448 unique asset CUSIP and 1,414,769 unique CUSIP-year observations reported in the general accounts' fixed-income portfolio across all the public traded life insurers from 1996 to 2018. As introduced in Section 1.2, insurers report accrued interests coupon payments and themarket price for each asset. This information can be used to infer asset return.

To check the validity of the inferred return, I cross check these return with the market return for trading assets that can be collected from other data vendors. Among all the fixed-income products, corporate bonds have the most accessible pricing data. As such, most of the cross-checking is done with corporate bonds. I collect corporate bond pricing data from four databases: Mergent FISD, Bloomberg, TRACE, and the BofAML indices. I collect quarterly clean prices, accrued interest and coupon payments from various sources, and aggregate quarterly to annual frequency for the bonds that have all 4 quarter observations.

FISD provides bond information including the offering date, the coupon rate, coupon frequency, and the date issuers stop paying coupons, if any. It is useful to back out coupon payments and accrued interest for each period, especially for Bloomberg and TRACE as they only report clean bond prices, but not accrued interest. Bank of American Merrill Lynch constructs corporate bond indices for investment grade and high yield bonds. The constituents of each index are based on an average of Moody's, S&P, and Fitch ratings. The indices are rebalanced monthly and are not necessarily balanced panels for deriving bond-month return. I aggregate the annual return for the bonds that are included in the index for the entire 12 months in each given year. For bonds that are not included in the BofAML indices, I search in Bloomberg and collect historical clean prices from 1996 to 2018 for the ones available. I merged FISD data to calculate accrued interest and coupon payments. TRACE is another commonly used database for corporate bond prices and it provides transaction data. Following Harris and Piwowar [2006], I drop all trades with a volume less than 100K, which are likely to be non-institutional investors. I then keep the last price record for each quarter as the quarter end clean price. Similarly, I merge it with the FISD data to calculate accrued interest and coupon payments. This order of search is consistent with the approach in Nozawa [2017].

I also collect treasury prices from CRSP and merge them with the FISD data to calculate accrued interest and coupon payments.

71% of the corporate bonds and 35% of the treasuries in my sample can be merged. However, as the datasets for fixed-income asset prices cover a shorter time period, the matching rate is lower for the whole panel. I winsorize both the market return $r_{j,t}^{CC}$ for asset $j$ at time $t$ held by firm $i$ and the filing inferred return $r_{i,j,t}$ at the 1% level for each calendar year and run the following regression to determine how accurate the calculated return is:

$$r_{i,j,t}^{CC} = \beta_0 + \beta_1 r_{i,j,t} + \alpha_t + \gamma_i + \epsilon_{i,j,t}.$$

The coefficient estimate for $\beta_1$ is 0.99, and the regression yields a 85% $R^2$. The estimation remains unchanged with or without year ($\alpha_t$) and/or firm ($\gamma_i$) fixed-effects . As the coefficient is less than one, firms tend to file relatively higher returns for the assets in their portfolio. Since the effect is not drastic, I use the inferred return for analysis in the rest of the paper.

### 1.9.4 Mortgage Loan Returns

Since insurers only file effective interest rates and amortized values for mortgage loans, I explain my calculations regarding the return on mortgage loans in this section. For loans that are in good standing, the fair value of a mortgage loan is the sum of its discounted future cash flows. To calculate the fair value of these loans, I back out the face value using the information on the acquired date and the maturity for each mortgage loan, assuming they amortize according to a standard annuity formula. I then discount each of the coupon payments using the respective yield curve to acquire the fair value. This methodology follows Begenau, Piazzesi, and Schneider [2015]. In particular, I calculate the coupon payment as the difference between the growth value of the amortized value from the last period and this period for a mortgage loan $i$ which was acquired $t$ years ago by the insurers:

$$C_{i,t} = B_{i,t-1}(1 + r_i) - B_{i,t},$$

where $C$ is the coupon payments, $B$ is the amortized value, $r$ is the effective interest rate and $t$ is the time since the mortgage loan is acquired.

I assume the annuity coupon as the average of the coupon calculated using each period's information:

$$C_i = \overline{C_{i,t}}$$

I can then back out the maturity for each loans= assuming the loan pays out the coupon as an annuity:

$$\frac{B_0 r_i}{C_i} = 1 - \frac{1}{(1+r_i)^{n_i}},$$

where $B_0$ is the book value reported at the time of acquisition or the first observable book value. I assume that $B_0$ is the face value of the mortgage loan. This is a fair assumption as insurance companies record their loans using the effective interest rate as the discounting rate (e.g., mentioned in Metlife 10K). Finally, I winsorize maturity cross sectionally at 5%. The average maturity of a mortgage loan held by an insurance company is 22 years.

I using the zero coupon rate for bonds that matured from 1 to 30 years from FED following Gürkaynak, Sack, and Wright [2007]. For cash flows that are estimated longer than 30 years, I the use 30 year rate.

For loans that are in the process of foreclosure, have interest payments overdue for over 90 days, or those being restructured, I calculate the value of the underlying collateral as the fair value of the mortgage loan. Panel B of Table 1.2 provides the relative weights of each type of loans. These default valuations are done by insurance companies at least once a year to ensure that the value of the mortgage loans is properly measured. The value of the land along with the date of the last appraisal is reported by 99.8% of these loans. I assume the mortgage loans are within the MSA of the insurers' subsidiaries and then use the housing price index from FHFA to estimate the fair value of the mortgage loan for each year.

The return on these mortgages is the sum of the changes in the fair value of the loans and interest return if there are any.

### 1.9.5 Bloomberg Barclays U.S. Total Return Indices

In this section, I explain the choice of index for each asset class and the components of each index. All of the information can be found on Bloomberg.

**Indices Used for Constructing Factors**

*Corporate High Yield Index (LF98TRUU)* measures the USD-denominated, high yield, fixed-rate corporate bond market. Securities are classified as high yield if the middle rating of Moody's, Fitch and S&P is Ba1/BB+/BB+ or below. Bonds from issuers with an emerging markets country of risk, based on Barclays EM country definition, are excluded.

*Treasury Index (LUATTRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Short Treasury Index (LT12TRUU)* measures the performance of the US Treasury bills, notes, and bonds under 1 year to maturity. STRIPS are excluded from the index because their inclusion would results in double-counting.

*Long Treasury Index (LUTLTRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 10 years or more to maturity.

**Indices Used as Proxies for Life Insurance Companies' Policy return** *Treasury: 1-3 Year Index (LT01TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 1-2.999 years to maturity. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Treasury: 3-5 Year Index (LT02TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 3-4.9999 years to maturity. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Treasury: 5-7 Year Index (LT03TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 5-6.9999 years to maturity. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Treasury: 7-10 Year Index (LT04TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 7-9.9999 years to maturity. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Intermediate Treasury Index (LT08TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with maturities of 1 to 9.9999 years to maturity.

**Indices Used to Mimic Life Insurance Companies' Assets**

*Corporate Index (LUACTRUU)* measures the investment grade, fixed-rate, taxable corporate bond market. It includes USD denominated securities publicly issued by US and non-US industrial, utility and financial issuers.

*Treasury: 5-7 Year Index (LT03TRUU)* measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury with 5-6.9999 years to maturity. Treasury bills are excluded by the maturity constraint, but are part of a separate Short Treasury Index. STRIPS are excluded from the index because their inclusion would result in double-counting.

*Municipal Bond Index (LMBITR)* covers the USD-denominated long-term tax exempt bond market. The index has four main sectors: state and local general obligation bonds, revenue bonds, insured bonds and prerefunded bonds.

*MBS Index (LUMSTRUU)* tracks fixed-rate agency mortgage backed pass-through securities guaranteed by Ginnie Mae (GNMA), Fannie Mae (FNMA), and Freddie Mac (FHLMC). The index is constructed by grouping individual TBA-deliverable MBS pools into aggregates or generics based on program, coupon and vintage. Table 1.16 summaries risk exposures for each of the Bloomberg Barclays US total return index.

## 1.10 Appendix: VaR

### 1.10.1 Derivation and Data

I derive the variance decomposition for the net business asset return in detail in this section. Following Vuolteenaho [1999], I assume that net financial assets ($E^{Fin}$), dividend to stockholders ($Div$), and market equity ($E$) are strictly positive. I also assume that the difference between log net financial assets($f$) and log market equity ($m$), and the different between log dividend ($d$) and log net financial assets are stationary. I can decompose the net financial assets as follows:

$$E_t^{Fin} = E_{t-1}^{Fin} + X_t^{Fin} + X_t^{Bus} - Div_t$$

where net financial assets this year equals net financial assets last year plus financial earnings ($X_t^{Fin}$) and the net business asset dividend paid to the net financial asset account ($X_t^{Bus}$), less the dividend paid to stock holders. Log equity return ($r_t$), log business-cash-flow return ($e_t^{Bus}$) and log net financial asset return ($e_t^{Fin}$) are defined as follows

$$\begin{aligned} r_t &\equiv \log(\frac{E_t + Div_t}{E_{t-1}}) = \log(1 + R_t) \\ e_t^{Bus} &\equiv \log(\frac{E_t^{Fin} + Div_t}{E_{t-1}^{Fin}}) - e_t^{Fin} \end{aligned}$$

where $e_t^{Fin} \equiv \log(1 + X_t^{Fin}/E_{t-1}^{Fin})$.

Substituting the dividend growth rate $\Delta d_t = d_t - d_{t-1}$, the log dividend-price $d_t - m_t$ and the log dividend-to-financial-asset ratio $d_t - f_t$, I have that

$$\begin{aligned} r_t &= \log\Big(\exp(d_t - m_t) + 1\Big) + \Delta d_t + d_{t-1} - m_{t-1} \\ e_t^{Bus} + e_t^{Fin} &= \log\Big(\exp(d_t - f_t) + 1\Big) + \Delta d_t + d_{t-1} - f_{t-1} \end{aligned}$$

Denoting the log financial-to-market ratio by $\theta_t = f_t - m_t$, the above functions can be log linearized around the log dividend-price and the log dividend-to-financial-asset ratio. In particular, note that:

$$e_t^{Bus} + e_t^{Fin} - r_t \approx \rho\theta_t - \theta_{t-1},$$

when dividend yield drops, the approximation becomes more accurate.

Following Vuolteenaho [2002], I estimate $\rho$ by the following regression, assuming that $\rho$ is a constant across time and firms:

$$\theta_{t-1} + e_t^{Bus} + e_t^{Fin} - r_t = \alpha + \rho\theta_t + \kappa_t$$

The regression results states that $\rho = 0.96$ with a standard error of 0.02. The intercept is -0.0003 with a standard error of 0.0075. $R^2$ is 0.98. This result is similar to the estimation in Vuolteenaho [2002]. The estimate is robust to using a subsample of firms for different time periods, and stays unchanged whether using the market or using only insurance companies. I work with de-meaned logs of the variables to deal with the estimation errors.

I iterate the equation to derive:

$$\begin{aligned}\theta_{t-1} &= -\sum_{j=0}^{\infty}\rho^j e_{t+j}^{Bus} + \sum_{j=0}^{\infty}\rho^j(r_{t+j} - e_{t+j}^{Fin}) + \sum_{j=0}^{\infty}\rho^j(\alpha + \kappa_{t+j}).\\ &= \frac{\alpha}{1-\rho} - \sum_{j=0}^{\infty}\rho^j e_{t+j}^{Bus} + \sum_{j=0}^{\infty}\rho^j(r_{t+j} - e_{t+j}^{Fin}) + \sum_{j=0}^{\infty}\rho^j\kappa_{t+j}\end{aligned}$$

This is true when $\rho < 1$ and $\rho^\infty\theta_\infty \to 0$.

I take the change in expectation of the above equation to get:

$$r_t - e_t^{Fin} - \mathbb{E}_{t-1}(r_t - e_t^{Fin}) = \Delta\mathbb{E}_t\sum_{j=0}^{\infty}\rho^j e_{t+j}^{Bus} - \Delta\mathbb{E}_t\sum_{j=1}^{\infty}\rho^j(r_{t+j} - e_{t+j}^{Fin}) + \epsilon_t$$

where $\Delta E_t$ denotes the change in expectations from $t-1$ to $t$. Defining the two return components as *business-cash-flow news* ($N_{cf}$) and *expected-business-return news* ($N_r$):

$$N_{cf,t} \equiv \Delta\mathbb{E}_t \sum_{j=0}^{\infty} \rho^j e^{Bus}_{t+j} + \epsilon_t$$
$$N_{r,t} \equiv \Delta\mathbb{E}_t \sum_{j=1}^{\infty} \rho^j (r_{t+j} - e^{Fin}_{t+j})$$

The unexpected business return can be high if expected business operation cash flow is high or expected business-cash-flow return is low.

The data used for the VAR decomposition for the market portfolio come from the CRSP-COMPUSTAT intersection. For the market portfolios, I study common stocks traded in NYSE, AMEX or Nasdaq. Following Vuolteenaho [2002], I require that all firms have non-missing book equity for $t+1$, $t-1$, $t-2$ and $t-3$. I exclude firms with $t-1$ market equity less than \$10 million and that book-to-market more than 100 or less than 1/100. Annual stock return is compounded from monthly return, recorded from the beginning of June to the end of May. I follow Fama and French [1993] to construct book equity, and use net income as the numerator when calculating ROE. I replace all ROE that is less than $-100\%$ by $-100\%$. In addition, I redefine the firm as a portfolio of 90% common stock and 10% Treasury bills to avoid the complication that could be caused by log transformations.

### 1.10.2 Panel VAR Parameter Estimates

### 1.10.3 Aggregate VAR

For the aggregate time series, I adopt two different specifications for the VAR(1). First, I consider a parsimonious VAR specification that connects directly to the main specification in the panel VAR, having the value-weighted log adjusted business return ($r - e^{Fin}$), the log financial-to-market ratio ($\theta$), and the log aggregate business-cash-flow return ($e^{Bus}$) as state variables. I dub this specification "the short VAR". Parameter estimates are provided in the Panel A of Table 1.18. I run the same aggregate VAR specification to decompose the aggregate equity market return, using log aggregate equity market return, log aggregate book-to-market ratio, and log aggregate ROE as state variables. The top plot of Figure 1.11 plots the model implied indirect business-cash-flow shocks to insurers and the model implied cash-flow shocks to the market portfolio. The point estimate of the correlation is 0.35 (t-stat 2.06).

The second aggregate VAR specification for insurers, which I refer to as "the long VAR" includes the value-weighted equity return ($r$), the aggregate financial return ($e^{Fin}$), the aggregate financial-to-market ratio ($\theta$), and the aggregate business-cash-flow return ($e^{Bus}$) as state variables. Define $e1' \equiv [1\ 0\ ...\ 0]$, $e2' \equiv [0\ 1\ ...\ 0]$ and

$$\lambda' \equiv e1'\rho\Gamma(I - \rho\Gamma)^{-1}$$

$$\mu' \equiv e2'\rho\Gamma(I - \rho\Gamma)^{-1}$$

The expected equity return news can then be conveniently expressed as $\lambda'\omega_t$ and the indirect business-cash-flow news as $(e1' + \lambda' + \mu')\omega_t$. To derive the direct measure, define $e3' \equiv [0\ 0\ ...\ 1]$. The direct business-cash-flow news is thus $e3'(I - \rho\Gamma)^{-1}$. Parameter estimates are provided in Panel B of Table 1.18. The direct and indirect estimate of business-cash-flow news are highly correlated, and the direct estimate is able to explain 93% of the indirect estimate of the business-cash-flow news. The bottom plot of Figure 1.11 plots the model implied indirect business-cash-flow shocks, and the model implied cash-flow shock for the aggregate market portfolio. The point estimate of the correlation is 0.46 (t-stat 2.28).

## 1.11 Appendix: Finite Horizon Cash-Flow Shocks

To address the concern with the VAR model having an infinite horizon, I confirm the fact that insurers' business operation cash flows are correlated with the market cash flows in a finite horizon setup. I define the value weighted cumulative return on business operations for insurance companies over the period of $l$ years as

$$e_t^{Bus,l} = \frac{\sum_{i\in I} E_{i,t-1}(\sum_{j=0}^{j=l} e_{i,j-l}^{Bus})}{\sum_{i\in I} E_{i,t-1}},$$

where $e^{Bus}$ is the log business-cash-flow return (formally defined in Appendix 1.10.1).

Similarly, define the value weighted cumulative ROE over the period of $l$ years for firms that are in the market portfolio as

$$e_t^{M,l} = \frac{\sum_k E_{k,t-1}(\sum_{j=0}^{j=l} e_{k,t-j}^{M})}{\sum_k E_{k,t-1}},$$

where $e^M$ is the log ROE.

Figure 1.12 illustrates the results for the five year cumulative business-cash-flow return for the life insurance sector, and the five year cumulative ROE return for the market portfolio. They are strongly positively correlated. This results is robust to using different lengths of horizons. In particular, I run the following regression for horizons as short as 1 year to as long as 7 years ($l = 1, 2, 3, 4, 5, 6, 7$),

$$\frac{e_t^{Bus,l}}{l} = a + b\frac{e_t^{M,l}}{l} + \epsilon_t,$$

where the coefficient $b$ captures the correlation between annualized cumulative insurers' business cash-flow shocks and the annualized market portfolio's cash flow shocks. The estimations (and standard deviation) of $b$ are provided in Table 1.19. The estimate stays unchanged and significant over different horizons.

## 1.12 Appendix: Direct Estimation of The Net Business Assets

Assume that the aggregate net business asset dividend follows an AR 1 specification,

$$\frac{CF^{Bus}_{t+1}}{E_t} = \rho\frac{CF^{Bus}_{t}}{E_{t-1}} + \delta^X_{t+1},$$

where $\rho$ is assumed to be constant over time, and $\delta^X$ is a normally distribute shock whose mean is not necessarily 0. Iterating the equation forward for $j$ periods, I get

$$\frac{CF^{Bus}_{t+j}}{E_{t+j-1}} = \rho^j\frac{CF^{Bus}_{t}}{E_{t-1}} + \sum_{k=1}^{j}\delta^X_{t+k}\rho^{k-1}.$$

Assume that the aggregate market equity grows at an exogenous rate and the cost of capital for each period is also a random shock with a positive mean:

$$\frac{E_{t+1}}{E_t} = \delta^G_{t+1}\ ;\ R_{t\to t+1} = \delta^R_{t+1}.$$

Note that $\delta^G$ is assumed to be a normally distributed shock with a positive mean, and it is mechanically correlated with $\delta^X$. The cost of capital reflects firms' financing costs and is also related to $\delta^G$ and $\delta^X$. The correlation matrix is not modeled explicitly.

The theoretical definition of the value of net business assets is the expected discounted future business operation cash flows. Normalizing the value of net business assets at time $t$ and time $t-1$ by market equity yields:

$$\frac{E^{Bus}_t + CF^{Bus}_t}{E_{t-1}} = \mathbb{E}_t\left(\sum_{j=0}^{\infty}\frac{CF^{Bus}_{t+j}}{E_{t+j-1}}\frac{E_{t+j-1}}{E_{t-1}}\frac{1}{R_{t\to t+j}}\right)$$

$$\frac{E^{Bus}_{t-1}}{E_{t-1}} = \mathbb{E}_{t-1}\left(\sum_{j=0}^{\infty}\frac{CF^{Bus}_{t+j}}{E_{t+j-1}}\frac{E_{t+j-1}}{E_{t-1}}\frac{1}{R_{t-1\to t+j}}\right)$$

Denote $\prod_{k=1}^{k=j}\delta^G_{t+k-1}/\prod_{k=1}^{k=j}\delta^R_{t+k} \equiv \gamma_{t,j}$, the net business asset value at time $t$, expressed as the net present value as future business operation cash flows, is:

$$\begin{aligned}\frac{E_t^{Bus}+CF_t^{Bus}}{E_{t-1}} &= \mathbb{E}_t\Big(\sum_{j=0}^{\infty}(\rho^j\frac{CF_t^{Bus}}{E_{t-1}}+\sum_{k=1}^{j}\delta_{t+k}^X\rho^{k-1})\gamma_{t,j}\Big)\\ &= \frac{CF_t^{Bus}}{E_{t-1}}\mathbb{E}_t\Big(\sum_{j=0}^{\infty}\rho^j\gamma_{t,j}\Big)+\mathbb{E}_t\Big(\sum_{j=1}^{\infty}\sum_{k=1}^{j}(\delta_{t+k}^X\rho^{k-1})\gamma_{t,j}\Big).\end{aligned}$$

Similarly the net business asset value at time $t-1$ is:

$$\begin{aligned}\frac{E_{t-1}^{Bus}}{E_{t-1}} &= \mathbb{E}_{t-1}\Big(\sum_{j=0}^{\infty}(\rho^{j+1}\frac{CF_{t-1}^{Bus}}{E_{t-2}}+\sum_{k=1}^{j}\delta_{t+k-1}^X\rho^{k-1})\gamma_{t-1,j}\Big)\\ &= \rho\frac{CF_{t-1}^{Bus}}{E_{t-2}}\mathbb{E}_{t-1}\Big(\sum_{j=0}^{\infty}\rho^j\gamma_{t-1,j}\Big)+\mathbb{E}_{t-1}\Big(\sum_{j=1}^{\infty}\sum_{k=1}^{j}(\delta_{t+k-1}^X\rho^{k-1})\gamma_{t-1,j}\Big).\end{aligned}$$

Assume that for any $t$, the expectations of the joint distribution of future shocks stay unchanged as follows:

$$\mathbb{E}_{t-1}\Big(\sum_{j=0}^{\infty}\rho^j\gamma_{t-1,j}\Big)=\mathbb{E}_t\Big(\sum_{j=0}^{\infty}\rho^j\gamma_{t,j}\Big)\equiv\mu$$
$$\mathbb{E}_{t-1}\Big(\sum_{j=1}^{\infty}\sum_{k=1}^{j}(\delta_{t+k-1}^X\rho^{k-1})\gamma_{t-1,j}\Big)=\mathbb{E}_t\Big(\sum_{j=1}^{\infty}\sum_{k=1}^{j}(\delta_{t+k}^X\rho^{k-1})\gamma_{t,j}\Big),$$

The business equity return can be measured as a scaler multiplied by the AR(1) shock to the net business asset dividend such that:

$$\frac{E_{t-1}^{Bus}}{E_{t-1}}R_t^{Bus}=\mu\sigma_t^X.$$

## 1.13 Appendix: Asset Management Before and After the Financial Crisis

Table 1.20 provides the results of for the coefficient estimates for Equation 16 for pre- and post-crisis sub-periods. Panel A reports the results for the pre-crisis period from 2002 to

2007, while Panel B presents the results for the post-crisis period from 2010 to 2018. Notably, insurers' investment portfolios exhibit difference tracking patterns before and after the financial crisis. While after the financial crisis insurers have higher betas on their respective asset class indices, this does not necessarily mean their portfolios become riskier as they also have higher R squares. This indicates that insurers load more significantly on fixed-income factors and hold more of the assets in the index. In the cross section, alphas are more significant after the financial crisis, but the magnitude remains low. Note that post the financial crisis, there is higher point estimates and lower variation in betas and R squares. This indicates that insurers' portfolios become more unified in that they do not take any risks outside of the index scope.

# Tables

**Table 1.1:** This table presents the breakdown for the assets and liabilities from the statutory annual filings of Metlife's largest subsidiary (NAIC Code 65978). The amounts are in millions of dollars. Ninety-six percent of the assets are investments that are reported at their marked-to-market value. Eighty-two percent of the liabilities are policy related balances whose market value is primarily exposed to risk-free term structure risks.

| Assets For MetLife 2019 (millions) | | Liabilities For MetLife 2019 (millions) | |
|---|---|---|---|
| Bonds | 143,598 | Aggregate reserve for life contract | 104,400 |
| Stocks | 1,931 | Aggregate reserve for accident and health | 23,303 |
| Mortgage loans | 58,011 | Liability for deposit-type contracts | 64,908 |
| Real estate | 1,408 | Contract Claims | 3,705 |
| Cash & other short term investments | 9,368 | Policyholders' dividends | 499 |
| Contract loans | 6,100 | Premiums received in advance | 367 |
| Other invested assets | 21,940 | Other contract liabilities | 3,055 |
| Receivables related to investments | 4,324 | Total policy liabilities | 200,237 |
| Total investments | 246,680 | Commissions, General expenses & taxes payable | 1,907 |
| Receivable related to products | 3,209 | Unearned investment income | 16 |
| Reinsurance | 2,277 | Miscellaneous | 43,477 |
| Net deferred tax asset | 1,418 | | |
| Software | 39 | | |
| Other assets | 2,917 | | |
| Total | 256,540 | Total | 245,637 |

**Table 1.2:** This table reports the main summary statistics for life insurance companies from 2000 to 2018. The dollar amounts are in billions and the counts for securities are in units. For each entry, I report the number of firm-year observations, as well as the mean, median, 25%, and 75% in the cross-section. The numbers in the brackets are the variable values as the ratio of the market capitalization.

| **Panel A: Financial Variables** | | | | | |
|---|---|---|---|---|---|
| | N | Mean | Median | 25% | 75% |
| Assets | 467 | 93.56 | 27.06 | 7.70 | 104.07 |
| Long-term Debt | 394 | 3.46 | 1.12 | 0.34 | 3.36 |
| Market Cap | 416 | 8.04 | 2.74 | 0.80 | 9.17 |
| Book Leverage | 459 | 11.62 | 8.44 | 6.64 | 15.32 |
| Market Leverage | 434 | 13.56 | 10.61 | 5.65 | 16.72 |
| Book to Market | 408 | 1.23 | 0.99 | 0.68 | 1.45 |
| # of Subsidiaries | 39 | 5.92 | 4.00 | 2.00 | 7.00 |

| **Panel B: Asset Portfolios** | | | | | |
|---|---|---|---|---|---|
| | N | Mean | Median | 25% | 75% |
| *B1: Tradable Assets* | | | | | |
| # of Securities | 443 | 3128 | 1929 | 1150 | 3797 |
| Corp Bonds % | 443 | 73.62% | 77.0% | 67.17% | 82.64% |
| Agency-Backed MBS % | 443 | 8.91% | 7.85% | 2.78% | 12.40% |
| Treasuries % | 443 | 4.56% | 2.94% | 1.40% | 6.03% |
| Municipal Bonds % | 437 | 3.18% | 1.66% | 0.87% | 3.19% |
| Equities % | 443 | 6.43% | 4.80% | 2.10% | 8.54% |
| Cash Equivalents % | 443 | 2.32% | 1.16% | 0.16% | 3.08% |
| *B2: Mortgage Loans* | | | | | |
| # of Securities | 338 | 698 | 181 | 39 | 725 |
| Good Standing % | 338 | 88.95 | 99.97 | 93.77 | 100 |
| In Process of Foreclosure % | 190 | 23.80 | 4.75 | 0.55 | 31.98 |

| **Panel C: Statutory Filings** | | | | | |
|---|---|---|---|---|---|
| | N | Mean | Median | 25% | 75% |
| *C1: Net Income Statement* | | | | | |
| Investment Earnings | 392 | 2.36 | 1.10 | 0.41 | 2.79 |
| *∼/Mkt Cap* | | [0.56] | [0.41] | [0.28] | [0.66] |
| Premiums | 392 | 7.73 | 3.08 | 0.81 | 8.29 |

| | | | | | |
|---|---|---|---|---|---|
| *~/Mkt Cap* | | [1.60] | [1.23] | [0.70] | [1.84] |
| Benefits | 392 | 2.87 | 0.83 | 0.25 | 3.16 |
| *~/Mkt Cap* | | [0.66] | [0.38] | [0.25] | [0.61] |
| Increase in Reserve | 392 | 1.53 | 0.74 | 0.21 | 1.91 |
| *~/Mkt Cap* | | [0.57] | [0.27] | [0.12] | [0.54] |
| Commissions | 392 | 0.60 | 0.40 | 0.12 | 0.85 |
| *~/Mkt Cap* | | [0.19] | [0.13] | [0.08] | [0.23] |
| *C2: Exhibit 1: premiums and annuity considerations* | | | | | |
| First + Single ($Prem^N$) | 392 | 3.86 | 1.37 | 0.26 | 3.74 |
| *~/Mkt Cap* | | [0.92] | [0.56] | [0.25] | [1.03] |
| Renewal ($Prem^O$) | 392 | 4.14 | 0.86 | 0.24 | 5.48 |
| *~/Mkt Cap* | | [0.78] | [0.54] | [0.30] | [0.84] |
| *C3: Analysis of Increases in Reserve* | | | | | |
| New policy reserve ($Pol^N$) | 392 | 5.31 | 1.52 | 0.58 | 3.90 |
| *~/Mkt Cap* | | [1.11] | [0.74] | [0.45] | [1.34] |
| Reserve released ($Pol^R$) | 392 | 4.27 | 0.91 | 0.36 | 2.48 |
| *~/Mkt Cap* | | [0.72] | [0.58] | [0.22] | [0.97] |
| *C4: Exhibit of Life-Amount of Insurance* | | | | | |
| In Force ($) | 392 | 316.54 | 55.25 | 20.95 | 175.14 |
| *~/Mkt Cap* | | [58.78] | [33.20] | [18.84] | [66.76] |
| Addition $ % | 392 | 17.15% | 15.41% | 11.17% | 21.98% |
| Lost $% | 392 | 13.20% | 11.79% | 8.31% | 16.14% |
| In Force (# thousands) | 392 | 2402 | 685 | 244 | 2529 |
| Addition #% | 392 | 12.18% | 6.56% | 3.95% | 12.71% |
| Lost #% | 392 | 12.97% | 8.31% | 6.23% | 12.76% |

**Table 1.3:** This table presents risk exposures of treasury index returns with different maturities. In particular, Column 1 reports risk exposures for the treasury index including treasuries whose maturities are between 1 to 3 years, Column 2 for the treasury index including treasuries whose maturities are between 3-5 years, Column 3 for the treasury index including treasuries whose maturities are between 5-7 years, Column 4 for treasury index including treasuries whose maturities are between 7-10 years and Column 5 for treasuries with maturities between 1-10 years. Robust Newey-West adjusted standard errors are shown in parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | T (1-3yr) | T (3-5yr) | T (5-7yr) | T (7-10yr) | T Intermediate |
| | (1) | (2) | (3) | (4) | (5) |
| Level | 1.095*** | 1.048*** | 1.029*** | 0.925*** | 1.044*** |
| | (0.052) | (0.036) | (0.040) | (0.022) | (0.031) |
| Slope | −0.390*** | −0.116*** | 0.041* | 0.236*** | −0.164*** |
| | (0.026) | (0.014) | (0.023) | (0.030) | (0.022) |
| Curvature | −0.255*** | 0.074*** | 0.097*** | 0.112*** | −0.070*** |
| | (0.027) | (0.019) | (0.024) | (0.039) | (0.024) |
| Credit | 0.018** | 0.020*** | 0.025*** | 0.016 | 0.011 |
| | (0.008) | (0.004) | (0.009) | (0.017) | (0.007) |
| Market | −0.013* | −0.017*** | −0.021** | −0.017 | −0.013*** |
| | (0.008) | (0.004) | (0.009) | (0.016) | (0.005) |
| SMB | 0.024*** | 0.023*** | 0.010 | −0.017 | 0.024*** |
| | (0.007) | (0.007) | (0.009) | (0.016) | (0.006) |
| HML | −0.013** | −0.030*** | −0.028*** | −0.020*** | −0.025*** |
| | (0.006) | (0.006) | (0.005) | (0.006) | (0.004) |
| Constant | −0.001 | 0.001 | 0.002 | 0.002 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) |
| Adjusted $R^2$ | 0.950 | 0.982 | 0.984 | 0.985 | 0.979 |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 1.4:** This table reports the risk loadings of insurers' aggregate market equity, net business assets, and net financial assets using quarterly data from 2001 to 2018, all normalized by the value of market equity. All of the factors are return of the respective tradable indices. Robust Newey-West adjusted standard errors are shown in parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

| | $R^E - R^f$ | | | $\frac{E^{Bus}}{E}(R^{Bus} - R^f)$ | | | $\frac{E^{Fin}}{E}(R^{Fin} - R^f)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| MKT | 1.32*** | 1.18*** | 1.28*** | 0.95*** | 1.52*** | 1.42*** | 0.59*** | −0.05 | −0.12 |
| | (0.21) | (0.16) | (0.10) | (0.20) | (0.22) | (0.24) | (0.18) | (0.14) | (0.10) |
| CRED | | 0.32 | −0.20* | | −1.12*** | −1.40*** | | 1.24*** | 1.15*** |
| | | (0.34) | (0.10) | | (0.41) | (0.21) | | (0.33) | (0.15) |
| SLOPE | | | 0.18 | | | 0.71*** | | | −0.64*** |
| | | | (0.18) | | | (0.26) | | | (0.13) |
| CURV | | | 1.31*** | | | 2.27*** | | | −1.25*** |
| | | | (0.23) | | | (0.35) | | | (0.25) |
| SMB | | | −0.07 | | | 0.34 | | | −0.37** |
| | | | (0.13) | | | (0.25) | | | (0.15) |
| HML | | | 0.99*** | | | 0.85*** | | | 0.08 |
| | | | (0.12) | | | (0.12) | | | (0.10) |
| Constant | 0.001 | −0.002 | 0.01 | −0.01 | −0.002 | 0.01 | 0.003 | −0.01 | 0.001 |
| | (0.01) | (0.01) | (0.005) | (0.01) | (0.01) | (0.01) | (0.01) | (0.004) | (0.01) |
| Adjusted $R^2$ | 0.61 | 0.61 | 0.81 | 0.30 | 0.39 | 0.62 | 0.31 | 0.61 | 0.73 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 1.5:** This table provides the risk loadings for insurers' aggregate net business asset returns and net financial asset returns (normalized by the value of market equity) in a few robustness settings. Panel A reports the risk exposure for the period excluding the financial crisis (2008 and 2009). Panel B presents the risk exposure using orthogonal factors, where $MKT^e$ is orthogonal to all fixed-income factors and $CRED^e$ is orthogonal to level, slope, and curvature. Panel C provides the risk exposure at an annual frequency where the return of all assets filed by insurers are included in the investment return. Robust Newey-West adjusted standard errors are shown in parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

***Panel A: Excluding Financial Crisis***

| | $\frac{E^{Bus}}{E}(R^{Bus} - R^f)$ | | | $\frac{E^{Fin}}{E}(R^{Fin} - R^f)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | 1.14*** | 1.30*** | 1.12*** | 0.27*** | 0.14 | 0.08 |
| | (0.19) | (0.24) | (0.16) | (0.06) | (0.11) | (0.09) |
| CRED | | −0.46 | −1.15*** | | 0.38* | 0.85*** |
| | | (0.46) | (0.22) | | (0.22) | (0.22) |
| SLOPE | | | 0.46** | | | −0.48*** |
| | | | (0.23) | | | (0.15) |
| CURV | | | 2.41*** | | | −1.13*** |
| | | | (0.37) | | | (0.34) |
| SMB | | | 0.35 | | | −0.40*** |
| | | | (0.24) | | | (0.13) |
| HML | | | 0.73*** | | | 0.07 |
| | | | (0.16) | | | (0.13) |
| Constant | −0.01 | −0.01 | 0.02* | 0.005 | 0.002 | −0.005 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.005) | (0.01) |
| Adjusted $R^2$ | 0.47 | 0.47 | 0.69 | 0.13 | 0.15 | 0.26 |

***Panel B: Orthogonal Factors***

| | $\frac{E^{Bus}}{E}(R^{Bus} - R^f)$ | | | $\frac{E^{Fin}}{E}(R^{Fin} - R^f)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $MKT^e$ | 1.61*** | 1.68*** | 1.16*** | −0.33 | −0.19 | −0.28 |
| | (0.26) | (0.26) | (0.21) | (0.35) | (0.18) | (0.24) |
| $CRED^e$ | | 0.54 | 0.49*** | | 1.15*** | 1.15*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | (0.36) | (0.18) | | (0.24) | (0.16) |
| $\text{SLOPE}^e$ | | | $-1.78^{***}$ | | | $-0.32$ |
| | | | (0.25) | | | (0.30) |
| $\text{CURV}^e$ | | | $-0.11$ | | | 0.06 |
| | | | (0.52) | | | (0.41) |
| $\text{SMB}^e$ | | | $0.58^{**}$ | | | $-0.46^{***}$ |
| | | | (0.23) | | | (0.18) |
| $\text{HML}^e$ | | | $0.89^{***}$ | | | $0.29^{***}$ |
| | | | (0.11) | | | (0.10) |
| Constant | 0.01 | $-0.01$ | $-0.01$ | $0.02^{*}$ | $-0.01^{*}$ | $-0.01$ |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Adjusted $R^2$ | 0.35 | 0.38 | 0.63 | 0.02 | 0.53 | 0.58 |

***Panel C: Annual Data with All Asset Classes***

| | $\frac{E^{Bus}}{E}(R^{Bus} - R^f)$ | | | $\frac{E^{Fin}}{E}(R^{Fin} - R^f)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | $1.06^{***}$ | $0.91^{***}$ | $1.10^{***}$ | $1.06^{***}$ | $0.44^{***}$ | $-0.06$ |
| | (0.17) | (0.17) | (0.08) | (0.33) | (0.14) | (0.10) |
| CRED | | 0.24 | $0.25^{**}$ | | $1.11^{***}$ | $1.40^{***}$ |
| | | (0.26) | (0.10) | | (0.34) | (0.09) |
| SLOPE | | | 0.08 | | | $-1.17^{***}$ |
| | | | (0.19) | | | (0.18) |
| CURV | | | $1.49^{***}$ | | | $-1.74^{***}$ |
| | | | (0.27) | | | (0.25) |
| SMB | | | $-0.83^{***}$ | | | $-0.20$ |
| | | | (0.22) | | | (0.16) |
| HML | | | $0.82^{***}$ | | | $-0.20^{***}$ |
| | | | (0.17) | | | (0.06) |
| Constant | $0.04^{*}$ | 0.03 | $0.04^{***}$ | $-0.01$ | $-0.02$ | $0.03^{*}$ |
| | (0.02) | (0.02) | (0.01) | (0.02) | (0.03) | (0.02) |
| Adjusted $R^2$ | 0.65 | 0.64 | 0.78 | 0.66 | 0.85 | 0.90 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

**Table 1.6:** This table presents risk loadings for net business asset dividends normalized by market equity and the AR(1) shock to net business asset dividends using quarterly data from 2001-2018. The factors are not in the form of excess returns. The AR shock is estimated as the demeaned residuals of:

$$\frac{CF^{Bus}_{t+1}}{E_t} = \rho \frac{CF^{Bus}_{t}}{E_{t-1}} + \delta^X_{t+1}$$

Robust Newey-West adjusted standard errors are shown in parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

| | $CF^{Bus}/E$ | | | $AR(1)$ shock | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | 0.23*** | 0.17*** | 0.29*** | 0.22*** | 0.13** | 0.20** |
| | (0.08) | (0.06) | (0.07) | (0.07) | (0.05) | (0.09) |
| Cred | | 0.13 | 0.13 | | 0.20 | 0.22 |
| | | (0.12) | (0.15) | | (0.12) | (0.16) |
| Level | | | 1.35 | | | 1.48 |
| | | | (1.53) | | | (1.29) |
| Slope | | | −0.46 | | | −0.61 |
| | | | (0.72) | | | (0.62) |
| Curv | | | −0.51 | | | −0.68 |
| | | | (0.66) | | | (0.60) |
| SMB | | | −0.14 | | | −0.05 |
| | | | (0.13) | | | (0.13) |
| HML | | | 0.13 | | | 0.09 |
| | | | (0.10) | | | (0.09) |
| Constant | −0.01 | −0.01 | −0.02*** | −0.004 | −0.01 | −0.02*** |
| | (0.01) | (0.01) | (0.01) | (0.005) | (0.01) | (0.01) |
| Adj $R^2$ | 0.14 | 0.13 | 0.14 | 0.14 | 0.15 | 0.13 |

**Table 1.7:** This table presents the risk loadings for the quantities of new insurance products sold using data from 2001-2018. The factors are not in the form of excess returns. In Panel A, the dependent variables are set to be the face value of new life insurance sold as a ratio of life insurance in force at the end of the last period ($\nabla^+$ Face Value, Columns 1-3), and the number of new life insurance policies sold as a ratio of the total number of life insurance policies at the end of the last period ($\nabla^+$ Number, Columns 4-6). In Panel B, the dependent variables are set to be the number of new annuity policies that are not related to defined benefit plans sold as a ratio of the total number of annuity insurance policies that are not related to defined benefit plans at the end of the last period ($\nabla^+$ Number (Ordinary), Columns 1-3), and the number of new annuity insurance policies related to defined benefit plans sold as a ratio of the total number of annuity insurance policies related to defined benefit plans at the end of the last period ($\nabla^+$ Number (DB), Columns 4-6). Robust Newey-West adjusted standard errors are shown in parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

***Panel A: Life insurance***

| | $\nabla^+$ Face Value | | | $\nabla^+$ Number | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | $-0.13^{***}$ | $-0.16^{***}$ | $-0.21^{***}$ | $-0.002$ | 0.04 | $-0.04$ |
| | (0.03) | (0.04) | (0.08) | (0.02) | (0.06) | (0.08) |
| CRED | | 0.05 | $-0.03$ | | $-0.06$ | $-0.04$ |
| | | (0.05) | (0.05) | | (0.08) | (0.08) |
| LEVEL | | | $0.71^{*}$ | | | $-1.36^{***}$ |
| | | | (0.39) | | | (0.30) |
| SLOPE | | | $-0.56^{***}$ | | | $0.55^{***}$ |
| | | | (0.13) | | | (0.12) |
| CURV | | | $-0.76^{***}$ | | | $0.53^{***}$ |
| | | | (0.17) | | | (0.17) |
| SMB | | | $0.37^{***}$ | | | $-0.13^{**}$ |
| | | | (0.04) | | | (0.05) |
| HML | | | 0.02 | | | $-0.01$ |
| | | | (0.07) | | | (0.08) |
| Constant | $0.14^{***}$ | $0.14^{***}$ | $0.14^{***}$ | 0.08 | $0.08^{*}$ | $0.11^{***}$ |
| | (0.01) | (0.01) | (0.02) | (0.07) | (0.05) | (0.02) |
| Adjusted $R^2$ | 0.27 | 0.23 | 0.52 | $-0.07$ | $-0.11$ | $-0.07$ |

***Panel B: Annuity***

| | $\nabla^+$ Number (Ordinary) | | | $\nabla^+$ Number (DB) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | $-0.06^{*}$ | $-0.12^{*}$ | $-0.02$ | $-0.04^{***}$ | $-0.01$ | $-0.08^{***}$ |
| | (0.03) | (0.07) | (0.06) | (0.01) | (0.03) | (0.03) |
| CRED | | 0.10 | 0.07 | | $-0.06$ | $-0.02$ |
| | | (0.10) | (0.04) | | (0.04) | (0.02) |
| LEVEL | | | $0.58^{*}$ | | | 0.03 |
| | | | (0.30) | | | (0.20) |
| SLOPE | | | $-0.10$ | | | $-0.14^{***}$ |
| | | | (0.13) | | | (0.05) |
| CURV | | | $-0.03$ | | | $-0.18^{**}$ |
| | | | (0.16) | | | (0.09) |
| SMB | | | $0.14^{**}$ | | | 0.05 |
| | | | (0.06) | | | (0.03) |
| HML | | | 0.01 | | | $-0.06^{***}$ |
| | | | (0.05) | | | (0.02) |
| Constant | $0.11^{***}$ | $0.11^{***}$ | $0.08^{***}$ | $0.08^{***}$ | $0.08^{***}$ | $0.08^{***}$ |
| | (0.01) | (0.01) | (0.01) | (0.004) | (0.005) | (0.01) |
| Adjusted $R^2$ | 0.04 | 0.07 | 0.08 | 0.06 | 0.08 | 0.29 |

**Table 1.8:** This table shows the risk loadings of the AR(1) shocks to the operation cash flows from new customers net of commissions and cash flows from existing customers, both normalized by market equity, using annual data from 2000 to 2018. Robust Newey-West adjusted standard errors are shown in the parentheses. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

| | $(CF^{New} - C)/E$ | | | $CF^{Old}/E$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | 0.15*** | 0.34*** | 0.40*** | 0.09 | 0.03 | 0.08 |
| | (0.05) | (0.10) | (0.09) | (0.38) | (0.13) | (0.14) |
| CRED | | −0.28*** | −0.12 | | 0.08 | 0.07 |
| | | (0.11) | (0.11) | | (0.11) | (0.05) |
| LEVEL | | | 2.13*** | | | 0.79 |
| | | | (0.26) | | | (0.53) |
| SLOPE | | | 0.21** | | | 0.13 |
| | | | (0.10) | | | (0.25) |
| CURV | | | 0.46** | | | 0.51 |
| | | | (0.23) | | | (0.32) |
| SMB | | | −0.69*** | | | −0.10 |
| | | | (0.10) | | | (0.10) |
| HML | | | 0.003 | | | −0.05 |
| | | | (0.14) | | | (0.11) |
| Constant | −0.002 | −0.002 | 0.03 | 0.01 | 0.01 | −0.05 |
| | (0.02) | (0.02) | (0.02) | (0.01) | (0.01) | (0.04) |
| Adj $R^2$ | 0.06 | 0.14 | 0.35 | −0.01 | −0.07 | −0.42 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table 1.9:** This table reports the panel regression results for

$$\frac{Y_{i,t}}{E_{i,t-1}} = \alpha + \beta_0 \frac{CF^{Old}_{i,t}}{E_{i,t-1}} + \beta_1 \frac{A^I_{i,t-1}}{E_{i,t-1}} R^I_{i,t} + \gamma_i + \eta_t + \epsilon_{i,t}.$$

The independent variables are profit made from existing customers, normalized by market equity ($CF^{Old}/E$), and investment returns scaled by the investment to equity ratio ($(A^I/E)R^I$). The dependent variable $Y$ is set to profit from new customers ($CF^{New}$, Columns 1-3) and minus of operation costs ($-C$, Columns 4-6). Coefficients are estimated using annual data from 2000 to 2018 for firms with at least 10 annual observations. Standard errors are clustered at firm level. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

| | $CF^{New}/E$ | | | $-C/E$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $CF^{Old}/E$ | $-0.32^{***}$ | $-0.14^{***}$ | $-0.14^{***}$ | $-0.01$ | 0.001 | $-0.001$ |
| | (0.04) | (0.05) | (0.03) | (0.02) | (0.03) | (0.02) |
| $(A^I/E)R^I$ | $-0.26^{***}$ | $-0.18^{***}$ | $-0.32^{***}$ | $-0.08^{***}$ | $-0.08^{***}$ | $-0.14^{**}$ |
| | (0.07) | (0.03) | (0.06) | (0.03) | (0.03) | (0.05) |
| Year FE | N | N | Y | N | N | Y |
| Firm FE | N | Y | Y | N | Y | Y |
| Adj $R^2$ | 0.26 | 0.72 | 0.75 | 0.03 | 0.55 | 0.67 |

**Table 1.10:** This table reports the regression coefficient for the asset return by asset class, on their respective index return as follows:

$$R_t^k - R_t^f = \alpha^k + \beta^k (IND_t^k - R_t^f) + \epsilon_t^k.$$

where $R_t^k$ is the value-weighted return for asset class $k$ and $IND_t^k$ is the index return for asset class $k$. I show the aggregate time series regressions results in Columns 1-3. I report the aggregate alpha, beta, and adjusted $R^2$ for the aggregate time series. I also estimate the model for each firm and report the cross-sectional results in Columns 4-9. For the cross-sectional regression, I restrict the sample to firms that have at least 10 annual observations. This leaves me with 19 firms. I report the cross-sectional mean of alpha (Column 4), and the number of firms that have significant alphas at 10% confident interval (Column 5). I also report cross-sectional beta mean and standard deviations (Columns 6 and 7), as well as the cross-sectional $R^2$ mean and standard deviations (Column 8 and 9).

***Panel A: 2000-2018***

| | Time Series | | | XS $\alpha$ | | XS $\beta$ | | XS $R^2$ | |
|---|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | Adj. $R^2$ | Mean | N | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Corporate Bonds (Barclays) | −0.001 | 0.929*** | 91.5% | 0.010 | 1 | 0.997 | 0.165 | 88.1% | 9.2% |
| | (0.004) | (0.064) | | | | | | | |
| Corporate Bonds (BofAML) | −0.000 | 0.864*** | 92.5% | 0.011 | 1 | 0.922 | 0.155 | 88.8% | 9.1% |
| | (0.004) | (0.064) | | | | | | | |
| Municipal Bonds | 0.011 | 0.844*** | 53.4% | 0.019 | 2 | 0.899 | 0.278 | 52.9% | 18.2% |
| | (0.010) | (0.177) | | | | | | | |
| Treasuries (5-7 yr) | 0.002 | 1.045*** | 71.1% | 0.018 | 6 | 0.710 | 0.410 | 40.4% | 27.6% |
| | (0.009) | (0.151) | | | | | | | |
| Agency-Backed MBS | 0.009 | 0.908*** | 58.2% | 0.017 | 6 | 0.897 | 0.290 | 51.1% | 17.2% |
| | (0.006) | (0.173) | | | | | | | |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 1.11:** This table provides the pricing results in the cross section. Columns 1-3 present results on equities using a combination of the Fama French 25 portfolios sorted on size and book to market and 10 momentum portfolios test assets. Columns 4-6 present on results on bonds using a combination of the 10 corporate bond portfolios sorted on yield spreads from Nozawa [2017] and 10 maturity-sorted government bonds portfolios from CRSP's "Fama Bond Portfolio" file with maturities in six month intervals up to five years. Each model is estimated as $\mathbb{E}[R^e] = \lambda_0 + \beta_{fac}\lambda_{fac}$, where $\lambda$ is the pricing factor and $\beta$ is the prices of factors that are reported in the table. HKM is the pricing factor from He, Kelly, and Manela [2017] and both the pricing factor and test asset returns are collected from the authors' personal website. MKT is the excess market return from French's website. The Fama-MacBeth t-statistics are reported in parenthesis. Panel A studies a shorter time period during which insurers' net business asset capital gains can be accurately measured using the dataset I construct for life insurers. Panel B studies a longer time period and uses the differences between changes in market equity and changes in book equity to proxy for net business asset capital gains. The equity test assets used in the longer sample period also includes the Fama French 25 portfolios sorted on investments and provabilities. Mean absolute pricing error (MAPE) is in percentage terms. Three stars represent significance at the 1% level, two stars represent significance at the 5% level, and one star represents significance at the 10% level.

***Panel A: 2001Q1-2012Q4 (Accurate Measure)***

| | *Test Portfolios: FF 25 + Mom 10* | | | *Test Portfolios: Corp Bonds* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta E^{Bus}/E$ | 0.068 | | $0.087^{*}$ | 0.067 | | $-0.093^{*}$ |
| | (1.561) | | (1.756) | (1.171) | | $(-1.644)$ |
| HKM | | 0.011 | $-0.003$ | | $0.068^{***}$ | $0.061^{**}$ |
| | | (0.427) | $(-0.110)$ | | (2.411) | (2.173) |
| MKT | 0.002 | $-0.002$ | 0.007 | 0.031 | $-0.006$ | $-0.031$ |
| | (0.107) | $(-0.095)$ | (0.375) | (1.592) | $(-0.343)$ | $(-1.371)$ |
| MAPE | 0.553 | 0.688 | 0.527 | 0.291 | 0.258 | 0.254 |
| $R^2$ | 0.302 | 0.005 | 0.316 | 0.583 | 0.706 | 0.714 |
| Assets | 35 | 35 | 35 | 20 | 20 | 20 |
| Quarters | 48 | 48 | 48 | 48 | 48 | 48 |

***Panel B: 1975Q1-2012Q4 (Proxies for Net Business Asset Capital Gains)***

| | *Test Portfolios: FF (25+25) Mom 10* | | | *Test Portfolios: Corp Bonds* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta E^{Bus}/E$ | $0.037^{*}$ | | $0.064^{***}$ | $0.074^{*}$ | | 0.068 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (1.745) | | (2.940) | (1.692) | | (1.442) |
| HKM | | 0.007 | $-0.033^{*}$ | | $0.063^{***}$ | $0.059^{***}$ |
| | | (0.334) | (−1.666) | | (2.655) | (2.442) |
| MKT | 0.0004 | −0.006 | −0.001 | $0.026^{**}$ | 0.011 | 0.017 |
| | (−0.039) | (−0.596) | (−0.059) | (2.058) | (0.821) | (1.089) |
| MAPE | 0.501 | 0.611 | 0.434 | 0.122 | 0.13 | 0.118 |
| $R^2$ | 0.255 | 0.040 | 0.419 | 0.833 | 0.812 | 0.828 |
| Assets | 60 | 60 | 60 | 20 | 20 | 20 |
| Quarters | 152 | 152 | 152 | 152 | 152 | 152 |

**Table 1.12:** This table presents the breakdown for operation income from the statutory annual filings of Metlife's largest subsidiary (NAIC Code 65978). The amounts are in millions of dollars.

| Profit For MetLife 2019 (millions) | | Cost For MetLife 2019 (millions) | |
|---|---|---|---|
| Premiums | 25,337 | Benefits | 35,102 |
| Net investment income | 10,817 | Increase in reserve | (1,301) |
| Miscellaneous Income | 426 | Policy Interest | 1,784 |
| | | Commissions | 653 |
| | | General expense | 3,003 |
| | | Taxes | 358 |
| Total | 36,580 | Total | 39,599 |

**Table 1.13:** This table presents the break-downs for the premiums from the statutory annual filings (*Exhibit 1: Premiums and Annuity Considerations*) of Metlife's largest subsidiary (NAIC Code 65978). The amounts are in millions of dollars.

| Premiums For MetLife 2019 (millions) | |
|---|---|
| **First Year** | |
| + Deferred, accured and uncollected | 2 |
| + Collected during the year | 4,896 |
| - Prior year (uncollected) | 2 |
| = Net | 4,896 |
| **Single** | 3,859 |
| **Renewal** | |
| + Deferred, accured and uncollected | 1,011 |
| + Collected during the year | 15,953 |
| - Prior year (uncollected) | 143 |
| = Net | 16,821 |

**Table 1.14:** This table presents the increases in statutory reserve from the statutory annual filings (*Analysis of Increases in Reserve*) of Metlife's largest subsidiary (NAIC Code 65978). The amounts are in millions of dollars.

| Reserve Increase For MetLife 2019 | | Reserve Decrease For MetLife 2019 | |
|---|---|---|---|
| Tabular net premiums | 13,647 | Tabular cost | 4,616 |
| Tabular interest | 4,431 | Reserve released by death | 1,206 |
| Other increase | 452 | Reserve released by other termination | 23,030 |
| Total | 18,530 | Total | 28,852 |

**Table 1.15:** This table presents the face value of the outstanding life insurance from the statutory annual filings (*Exhibit of Life-Amount of Insurance*) of Metlife's largest subsidiary (NAIC Code 65978). The amounts are in millions of dollars.

| Increase For MetLife 2019 (millions) | | Decrease For MetLife 2019 (millions) | |
|---|---|---|---|
| Issued during year | 122,962 | Death | 11,321 |
| Revived during year | 1,305 | Maturity | 118 |
| Reinsurance assumed | 76,852 | Expiry | 16,954 |
| | | Surrender | 10,465 |
| | | Lapse | 19,285 |
| | | Conversion | 27 |
| | | Decreased | 77,888 |
| Total | 201,119 | Total | 136,058 |

**Table 1.16:** This table reports risk exposures of fixed income indices for each asset class. The Newey-West robust standard errors are reported in the parentheses.

| | Corp Bond | Muni Bond | Treasury (5-7 yr) | Agency-backed MBS |
|---|---|---|---|---|
| Level | 0.636 | −0.508 | 1.253*** | 0.767** |
| | (0.548) | (0.492) | (0.112) | (0.349) |
| Slope | 0.031 | 0.455* | −0.075 | −0.097 |
| | (0.282) | (0.250) | (0.052) | (0.158) |
| Curvature | −0.017 | 0.245 | −0.025 | −0.153 |
| | (0.263) | (0.274) | (0.048) | (0.139) |
| Credit | 0.462*** | 0.345*** | 0.025*** | 0.135*** |
| | (0.021) | (0.058) | (0.009) | (0.028) |
| Market | −0.056 | −0.115*** | −0.019** | −0.044 |
| | (0.038) | (0.032) | (0.009) | (0.027) |
| SMB | −0.059 | −0.140*** | 0.009 | 0.019 |
| | (0.039) | (0.038) | (0.009) | (0.036) |
| HML | 0.015 | 0.018 | −0.028*** | −0.011* |
| | (0.020) | (0.046) | (0.005) | (0.006) |
| Constant | −0.001 | 0.018** | 0.001 | 0.005 |
| | (0.006) | (0.008) | (0.003) | (0.008) |
| Adjusted $R^2$ | 0.849 | 0.716 | 0.983 | 0.768 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 1.17:** This table provides the panel VAR (1) results for the equity return news decomposition. Panel A, B and D use the insurers' sample with 176 firm year observations from 2001-2017. Panel C uses the market sample with 13569 firm-year observations from 2001 to 2017. The VAR specialization is as follow:

$$z_{i,t} = \Gamma z_{i,t-1} + \omega_{i,t},\ \Sigma = \omega_{i,t}'\omega_{i,t}$$

Panel A presents the results decomposing insurers' total equity return into total cash-flow news and total expected-return news, using market-adjusted (annually demean) log stock return ($\hat{r}_{i,t}$), log total income return ($\hat{e}_{i,t}^{Fin} + \hat{e}_{i,t}^{Bus}$) and log financial-to-market ($\hat{\theta}_{i,t}$) as state variables. The variance of cash-flow shocks explains 90% of the total variance to unexpected shocks. Panel B reports the results decomposing insurers' business return into business-cash-flow news and expected-business-return news, using market-adjusted (annually demean) log adjusted business return ($\hat{r}_{i,t} - \hat{e}_{i,t}^{Fin}$), log business-cash-flow returns ($\hat{e}_{i,t}^{Bus}$) and log financial-to-market ($\hat{\theta}_{i,t}$) as state variables. The expected-business-return news standard deviation implied by this specification is 12% while the business-cash-flow-news standard deviation is 20%. The variance of business-cash-flow shocks explains 74% of the total variance to unexpected shocks. Panel C presents the results decomposing the equity return of firms in the market portfolio into cash-flow news and expected-return news, using market-adjusted (demean within industry) log stock return ($\tilde{r}_{k,t}$), log ROE ($\tilde{e}_{k,t}$) and log book-to-market ($\tilde{\theta}_{k,t}$) as state variables. Finally, Panel D reports a similar specification to Panel B except that all of the state variables are cross-sectional demeaned within the panel.

| | *Panel A: Insurers' Total Equity Return* | | | | | |
|---|---|---|---|---|---|---|
| | | $\Gamma$ | | | $\Sigma$ | |
| | $\hat{r}_{t-1}$ | $\hat{\theta}_{t-1}$ | $\hat{e}_{t-1}$ | $\hat{r}_{t-1}$ | $\hat{\theta}_{t-1}$ | $\hat{e}_{t-1}$ |
| $\hat{r}_t$ | -0.0615 | 0.0392 | -0.0134 | 0.0365 | -0.0306 | -0.0067 |
| | (0.0872) | (0.0472) | (0.0206) | | | |
| $\hat{\theta}_t$ | -0.0816 | 0.7477 | -0.0270 | -0.0306 | 0.0727 | 0.0390 |
| | (0.1365) | (0.0823) | (0.0295) | | | |
| $\hat{e}_t$ | 0.0321 | -0.3099 | 0.5393 | -0.0067 | 0.0390 | 0.3402 |
| | (0.2513) | (0.1347) | (0.1256) | | | |

| | *Panel B: Insurers' Adjusted Business Return* | | | | | |
|---|---|---|---|---|---|---|
| | | $\Gamma$ | | | $\Sigma$ | |
| | $\hat{r}_{t-1} - \hat{e}_{t-1}^{Fin}$ | $\hat{\theta}_{t-1}$ | $\hat{e}_{t-1}^{Bus}$ | $\hat{r}_{t-1} - \hat{e}_{t-1}^{Fin}$ | $\hat{\theta}_{t-1}$ | $\hat{e}_{t-1}^{Bus}$ |
| $\hat{r}_t - \hat{e}_t^{Fin}$ | -0.1793 | 0.0924 | 0.0479 | 0.0580 | -0.0478 | 0.0267 |
| | (0.1210) | (0.0673) | (0.0339) | | | |
| $\hat{\theta}_t$ | 0.3054 | 0.8317 | -0.0008 | -0.0478 | 0.0674 | -0.0022 |
| | (0.1314) | (0.0803) | (0.0307) | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\hat{e}_t^{Bus}$ | 0.4029<br>(0.1857) | -0.1071<br>(0.0995) | 0.6163<br>(0.0877) | 0.0267 | -0.0022 | 0.3189 |

*Panel C: Market Portfolios' Total Equity Return (XS De-meaned)*

| | $\Gamma$ | | | $\Sigma$ | | |
|---|---|---|---|---|---|---|
| | $\tilde{r}_{t-1}$ | $\tilde{e}_{t-1}$ | $\tilde{\theta}_{t-1}$ | $\tilde{r}_{t-1}$ | $\tilde{e}_{t-1}$ | $\tilde{\theta}_{t-1}$ |
| $\tilde{r}_t$ | -0.0504<br>(0.0108) | 0.5061<br>(0.0461) | 0.1390<br>(0.0075) | 0.0927 | -0.0721 | -0.0038 |
| $\tilde{e}_t$ | -0.0135<br>(0.0058) | 0.3560<br>(0.0314) | -0.0687<br>(0.0048) | -0.0721 | 0.1162 | 0.0016 |
| $\tilde{\theta}_t$ | 0.0283<br>(0.0115) | -0.5178<br>(0.0450) | 0.7482<br>(0.0080) | -0.0038 | 0.0016 | 0.0290 |

*Panel D: Insurers' Adjusted Business Return (XS De-meaned)*

| | $\Gamma$ | | | $\Sigma$ | | |
|---|---|---|---|---|---|---|
| | $\tilde{r}_{t-1} - \tilde{e}^F_{t-1}$ | $\tilde{e}^B_{t-1}$ | $\tilde{\theta}_{t-1}$ | $\tilde{r}_{t-1} - \tilde{e}^F_{t-1}$ | $\tilde{e}^B_{t-1}$ | $\tilde{\theta}_{t-1}$ |
| $\tilde{r}_t - \tilde{e}^F_t$ | -0.1773<br>(0.1926) | 0.3361<br>(0.1200) | 0.0162<br>(0.0380) | 0.0927 | -0.0721 | -0.0038 |
| $\tilde{e}^B_t$ | 0.0171<br>(0.0482) | 0.7544<br>(0.1330) | -0.0725<br>(0.0280) | -0.0721 | 0.1162 | 0.0016 |
| $\tilde{\theta}_t$ | 0.4344<br>(0.1230) | -0.3597<br>(0.1097) | 0.8031<br>(0.0454) | -0.0038 | 0.0016 | 0.0290 |

**Table 1.18:** This table provides the aggregate VAR (1) results for the equity return news decomposition. Panels A and B use the insurers' sample with 176 firm year observations from 2001-2017. Panel C uses the market sample with 13,569 firm-year observations from 2001 to 2017. The VAR specification is as follows:

$$z_{i,t} = \Gamma z_{i,t-1} + \omega_{i,t},\ \Sigma = \omega'_{i,t}\omega_{i,t}.$$

Panel A presents the short aggregate VAR estimation results decomposing insurers' market business return into business-cash-flow news and expected-business return news, using aggregate log adjusted business return ($r_t - e_t^{Fin}$), log aggregate business cash flow returns ($e_t^{Bus}$) and log aggregate financial-to-market ($\theta_t$) as state variables. Panel B presents the long aggregate VAR estimation results decomposing insurers' market equity return into financial cash-flow news, business cash-flow news and expected-return news, using aggregate log stock return($r_t$), log aggregate net financial asset return ($e_t^{Fin}$), log aggregate business-cash-flow return ($e_t^{Bus}$) and log financial-to-market ($\theta_t$) as state variables. Panel C presents the aggregate VAR estimation results decomposing equity return of firms in the market portfolio into cash-flow news and expected-return news, using aggregate log stock return ($r_t$), aggregate log ROE ($e_t$) and aggregate log book-to-market ($\theta_t$) as state variables.

| | *Panel A: Short Aggregate VAR for Insurers* | | | | | | |
|---|---|---|---|---|---|---|---|
| | | $\Gamma$ | | | | $\Sigma$ | |
| | Constant | $r_{t-1} - e_{t-1}^{Fin}$ | $\theta_{t-1}$ | $e_{t-1}^{Bus}$ | $r_{t-1} - e_{t-1}^{Fin}$ | $\theta_{t-1}$ | $e_{t-1}^{Bus}$ |
| $r_t - e_t^{Fin}$ | -0.1983 | -0.0734 | 0.3970 | 0.9637 | 0.0402 | -0.0353 | -0.0021 |
| | (0.0678) | (0.0464) | (0.0673) | (0.2821) | | | |
| $\theta_t$ | 0.0801 | -0.1128 | 0.4079 | -1.0601 | -0.0353 | 0.0639 | -0.0014 |
| | (0.0806) | (0.1511) | (0.1164) | (0.3271) | | | |
| $e_t^{Bus}$ | $-0.0139$ | -0.0481 | 0.1838 | -0.3487 | -0.0021 | -0.0014 | 0.0091 |
| | (0.0196) | (0.0519) | (0.0273) | (0.1305) | | | |

| | *Panel B: Long Aggregate VAR for Insurers* | | | | |
|---|---|---|---|---|---|
| | | | $\Gamma$ | | |
| | Constant | $r_{t-1}$ | $e_{t-1}^{Fin}$ | $\theta_{t-1}$ | $e_{t-1}^{Bus}$ |
| $r_t$ | 0.0364 | -0.1483 | -0.0230 | 0.3845 | -0.1558 |
| | (0.0187) | (0.0731) | (0.1073) | (0.0508) | (0.1161) |
| $e_t^{Fin}$ | 0.2480 | -0.0857 | -0.1308 | -0.0435 | -0.8468 |
| | (0.0255) | (0.0914) | (0.0814) | (0.0496) | (0.2291) |
| $\theta_t$ | 0.1698 | -0.4111 | -0.2681 | 0.4699 | -0.5077 |
| | (0.0265) | (0.4319) | (0.2823) | (0.0666) | (0.3635) |

| | | | | | |
|---|---|---|---|---|---|
| $e_t^{Bus}$ | -0.0389 | 0.0269 | 0.2062 | 0.1586 | -0.2835 |
| | (0.0203) | (0.0462) | (0.0881) | (0.0405) | (0.1264) |

| | $\Sigma$ | | | |
|---|---|---|---|---|
| | $r_{t-1}$ | $e_{t-1}^{Fin}$ | $\theta_{t-1}$ | $e_{t-1}^{Bus}$ |
| $r_t$ | 0.0204 | 0.0008 | -0.0125 | 0.0020 |
| $e_t^{Fin}$ | 0.0008 | 0.0240 | 0.0264 | 0.0037 |
| $\theta_t$ | -0.0125 | 0.0264 | 0.0621 | -0.0010 |
| $e_t^{Bus}$ | 0.0020 | 0.0037 | -0.0010 | 0.0128 |

*Panel C: Aggregate VAR for the Market Portfolio*

| | $\Gamma$ | | | | $\Sigma$ | | |
|---|---|---|---|---|---|---|---|
| | Constant | $r_{t-1}$ | $\theta_{t-1}$ | $e_{t-1}$ | $r_{t-1}$ | $\theta_{t-1}$ | $e_{t-1}$ |
| $r_t$ | -0.0431 | -0.1562 | 0.2444 | 3.0487 | 0.0047 | -0.0074 | -0.0002 |
| | (0.1280) | (0.0753) | (0.0433) | (0.9770) | | | |
| $\theta_t$ | 0.1433 | -0.0199 | 0.6933 | -3.7267 | -0.0074 | 0.0152 | 0.0013 |
| | (0.2167) | (0.1814) | (0.0785) | (1.7704) | | | |
| $e_t$ | 0.0461 | -0.0911 | -0.0004 | 0.5870 | -0.0002 | 0.0013 | 0.0004 |
| | (0.0223) | (0.0429) | (0.0205) | (0.1089) | | | |

**Table 1.19:** This table reports the regression coefficients for the following regression:

$$\frac{e_t^{Bus,l}}{l} = a + b\frac{e_t^{M,l}}{l} + \epsilon_t.$$

where the dependent variable is insurance companies' long term cumulative business-cash-flow return, and the independent variable is the long term market cumulative ROE. $l$ represents the number of years that the long term return is cumulated over.
The coefficient is estimated using quarterly data from 2001 to 2018, and the robust Newey-West adjusted standard errors are in parentheses.

| $l$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| b | 1.39 | 1.23 | 1.28 | 1.28 | 1.05 | 0.72 | 0.69 |
| s.e. | (0.90) | (0.59) | (0.36) | (0.22) | (0.23) | (0.35) | (0.36) |

**Table 1.20:** This table reports the regression coefficient for the asset return by asset class, on their respective index return as follows:

$$R_t^k - R_t^f = \alpha^k + \beta^k(IND_t^k - R_t^f) + \epsilon_t^k.$$

where $R_t^k$ is the value-weighted return for asset class $k$ and $IND_t^k$ is the index return for asset class $k$. I show the aggregate time series regressions results in Columns 1-3. I report the aggregate alpha, beta, and adjusted $R^2$ for the aggregate time series. I also estimate the model for each firm and report the cross-sectional results in Columns 4-9. For the cross-sectional regression, I restrict the sample to firms that have at least 10 annual observations. This leaves me with 19 firms. I report the cross-sectional mean of alpha (Column 4), and the number of firms that have significant alphas at 10% confident interval (Column 5). I also report cross-sectional beta mean and standard deviations (Columns 6 and 7), as well as the cross-sectional $R^2$ mean and standard deviations (Column 8 and 9). I report the results for pre-crisis (Panel A, 2000-2007) and the post-crisis (Panel B, 2010-2018) separately. For the pre- and post-crisis regressions, I restrict the subsample to firms with at least 5 annual observations.

| | Time Series | | | XS $\alpha$ | | XS $\beta$ | | XS $R^2$ | |
|---|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | Adj. $R^2$ | Mean | N | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ***Panel A: Pre-Crisis 2000-2007*** | | | | | | | | | |
| Corporate Bonds (Barclays) | 0.002 | 0.655*** | 80.6% | 0.011 | 1 | 0.718 | 0.139 | 76.2% | 14.5% |
| | (0.006) | (0.112) | | | | | | | |
| Corporate Bonds (BofAML) | 0.001 | 0.633*** | 78.8% | 0.010 | 1 | 0.696 | 0.137 | 74.8% | 14.9% |
| | (0.006) | (0.114) | | | | | | | |
| Municipal Bonds | 0.008 | 0.559*** | 55.7% | 0.003 | 2 | 0.690 | 0.331 | 48.9% | 26.7% |
| | (0.007) | (0.168) | | | | | | | |
| Treasuries (5-7 yr) | 0.000 | 0.978*** | 90.7% | −0.004 | 1 | 0.636 | 0.299 | 53.1% | 34.7% |
| | (0.030) | (0.110) | | | | | | | |
| Agency-Backed MBS | 0.009 | 0.490*** | 34.0% | 0.022 | 4 | 0.647 | 0.415 | 36.3% | 28.5% |
| | (0.008) | (0.216) | | | | | | | |
| ***Panel B: Post-Crisis 2010-2018*** | | | | | | | | | |
| Corporate Bonds (Barclays) | 0.005 | 0.946*** | 96.5% | 0.009 | 6 | 1.010 | 0.218 | 92.3% | 8.2% |
| | (0.006) | (0.112) | | | | | | | |
| Corporate Bonds (BofAML) | 0.004 | 0.918*** | 95.4% | 0.008 | 4 | 0.974 | 0.207 | 91.1% | 7.5% |
| | (0.004) | (0.070) | | | | | | | |
| Municipal Bonds | 0.006 | 1.486*** | 87.1% | 0.016 | 1 | 1.425 | 0.438 | 83.8% | 8.5% |
| | (0.010) | (0.177) | | | | | | | |
| Treasuries (5-7 yr) | 0.002 | 1.521*** | 72.5% | 0.025 | 3 | 1.247 | 0.598 | 68.0% | 21.0% |
| | (0.016) | (0.323) | | | | | | | |
| Agency-Backed MBS | 0.009 | 1.468*** | 94.7% | 0.015 | 9 | 1.343 | 0.558 | 82.8 % | 14.4% |
| | (0.004) | (0.123) | | | | | | | |

*Note:* *p<0.1; **p<0.05; ***p<0.01

# Figures

**Figure 1.1:** This figure plots one year rolling aggregate market equity CAPM betas using monthly equity return data for banks defined as when the first two digits of the SIC code equal 60 (depository institutions), 61 (non-depository credit institutions ), or 62 (broker-dealers), along with the aggregate market equity CAPM betas for life insurers. The horizontal dashed line crosses the y-axis at 1.

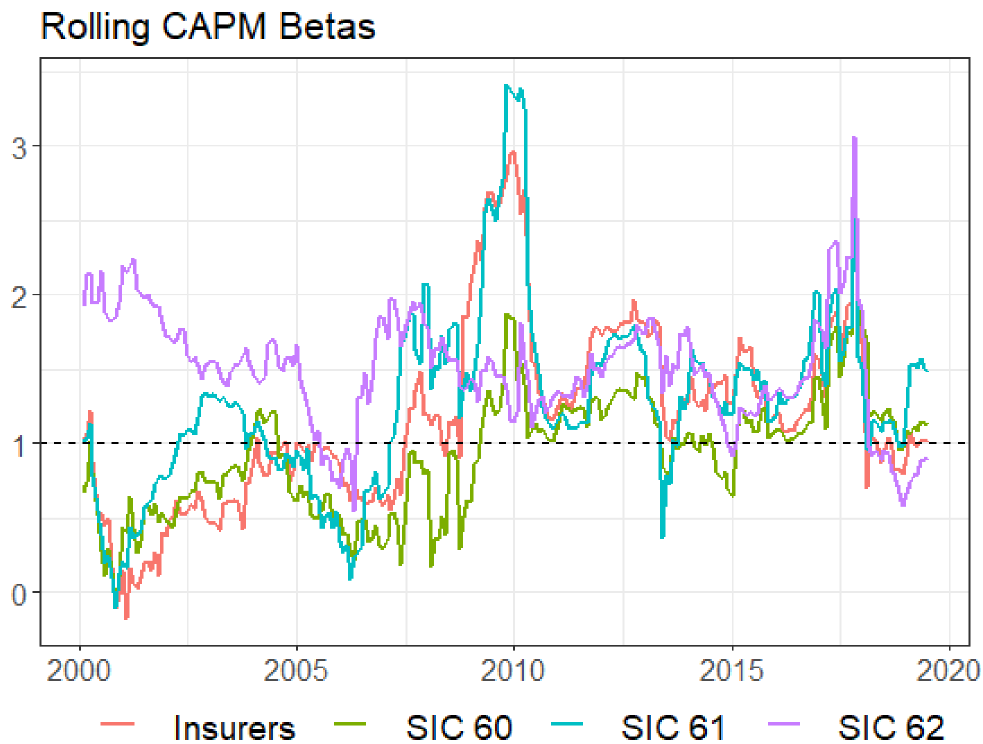
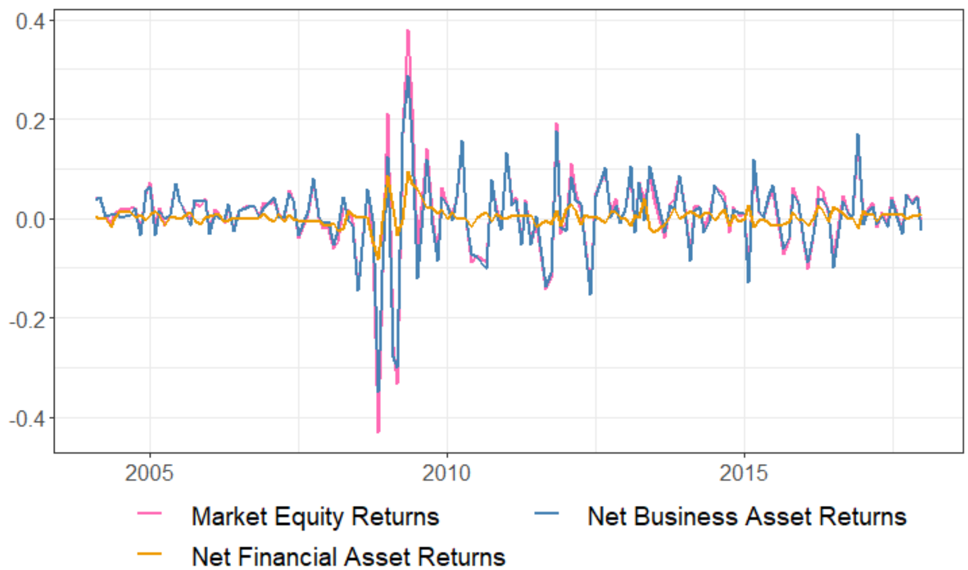


**Figure 1.2:** The top figure provides the time series of aggregate market equity returns ($R^E$), aggregate net business asset returns ($R^{Bus}E^{Bus}/E$), and aggregate net financial asset returns ($R^{Fin}E^{Fin}/E$) for life insurers. The bottom figure provides the one year aggregate rolling CAPM beta using monthly data for insurers' aggregate market equity returns ($R^E$), aggregate net business asset returns ($R^{Bus}E^{Bus}/E$), and aggregate net financial asset returns ($R^{Fin}E^{Fin}/E$).



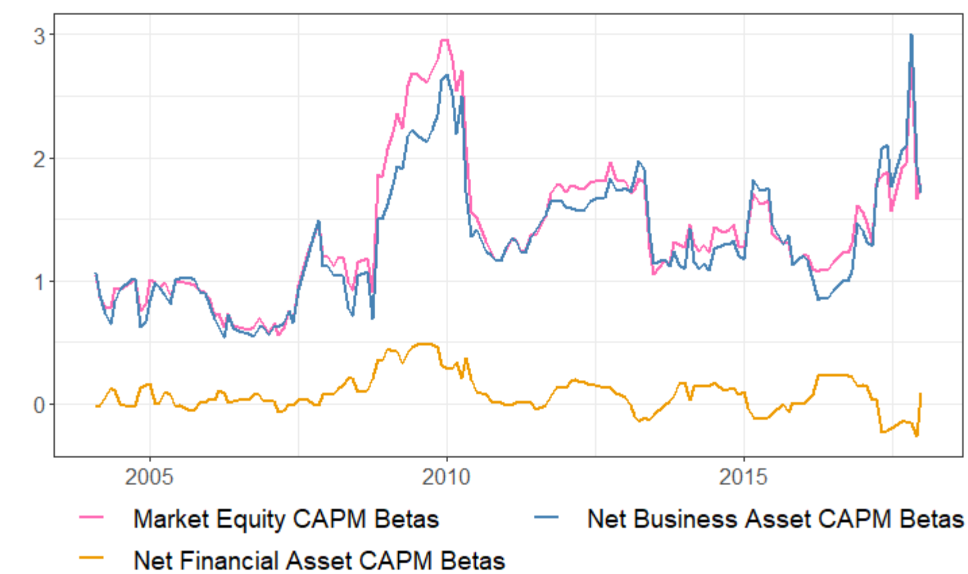



**Figure 1.3:** This figure reports simplified balance sheet components for a representative life insurance company. The total financial investment is denoted as $A^I$. The liabilities can be divided into financial obligations to debt holders ($D$) and business obligations to policy holders ($Pol$). The residual is defined as the net financial assets ($E^{Fin}$).

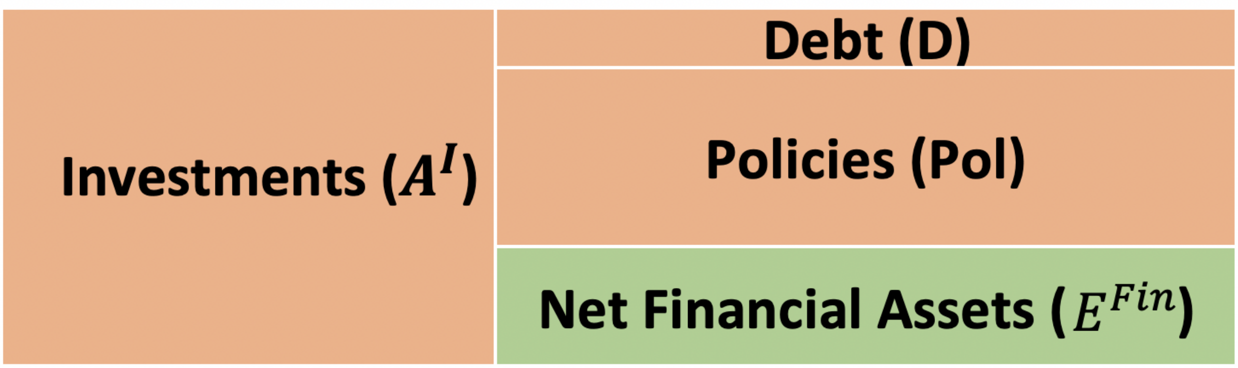


**Figure 1.4:** This figure presents single factor betas for insurers' market equity and net financial assets in the cross section. Each dot represents one firm in the sample, and the limits for the x-axis and the y-axis are set to be identical. The left plot provides the cross-sectional market equity CAPM betas (pink), net business asset CAPM betas (blue) on the y-axis and the net financial assets CAPM betas on the x-axis. In particular, the betas are estimated as

$$R_t^E - R_t^f = \alpha + \beta_i^{MKT,E} MKT_t + \epsilon_{i,t}$$
$$\frac{E_{t-1}^{Fin}}{E_{t-1}}(R_t^{Fin} - R_t^f) = \alpha + \beta_i^{MKT,Fin} MKT_t + \epsilon_{i,t}$$
$$\frac{E_{t-1}^{Bus}}{E_{t-1}}(R_t^{Bus} - R_t^f) = \alpha + \beta_i^{MKT,Bus} MKT_t + \epsilon_{i,t}$$

The right plot provides the cross-sectional market equity single factor credit betas (pink) and net business asset single factor credit betas (blue) on the y-axis, and the net financial assets single factor credit betas on the x-axis. In particular, the betas are estimated as:

$$R_t^E - R_t^f = \alpha + \beta_i^{CRED,E} CRED_t + \epsilon_{i,t}$$
$$\frac{E_{t-1}^{Fin}}{E_{t-1}}(R_t^{Fin} - R_t^f) = \alpha + \beta_i^{CRED,Fin} CRED_t + \epsilon_{i,t}$$
$$\frac{E_{t-1}^{Bus}}{E_{t-1}}(R_t^{Bus} - R_t^f) = \alpha + \beta_i^{CRED,Bus} CRED_t + \epsilon_{i,t}$$

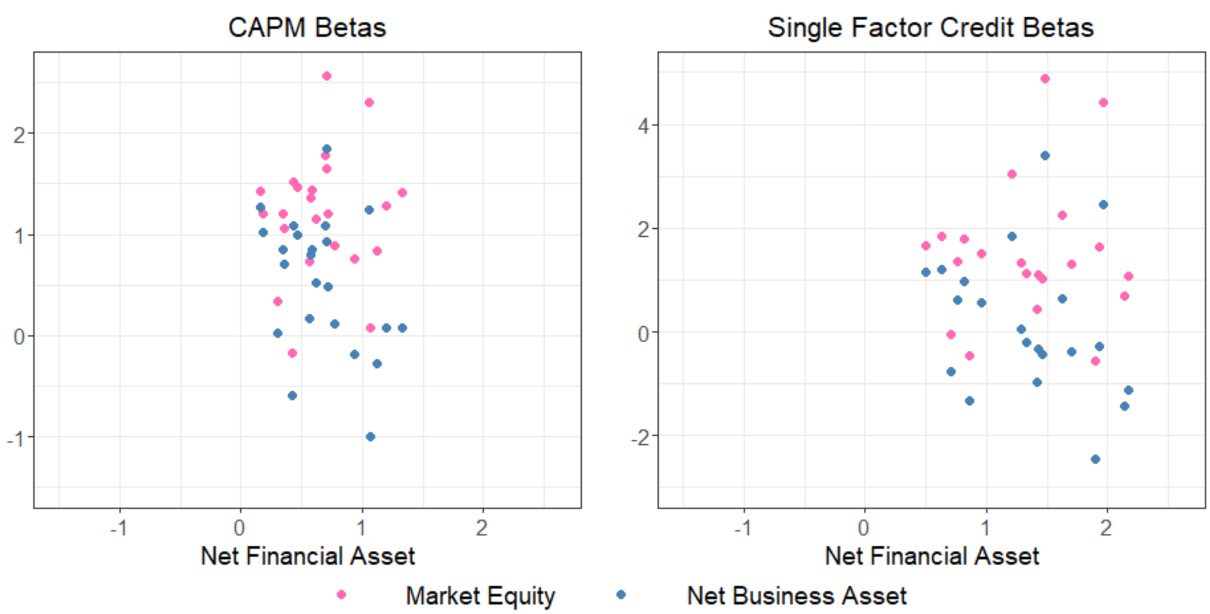


**Figure 1.5:** This figure presents the average asset weight level and active adjustments for different asset classes. The asset weight level $\omega$ for asset class $k$ is defined as the total market value $MV$ of assets belong to $k$ as a ratio of the size of total investments. For firm $i$ at time $t$, it can be expressed as

$$\omega_{i,t}^{k} = \frac{MV_{i,k,t}}{\sum_{j \in k} MV_{i,j,t}}.$$

The active adjustments are then defined as

$$\Delta\omega_{i,t}^{k} = \omega_{i,t}^{k} - \omega_{i,t-1}^{k} R_{i,t}^{k} / \overline{R_{i,t}^{k}}$$

where the first term is the asset class weights at the end of time $t$, and the second term is the passive asset class weights after realization of the current period return. In particular,

$$\omega_{i,t-1}^{k} R_{i,t}^{k} / \overline{R_{i,t}^{k}} = \frac{\sum_{j \in k} MV_{i,j,t-1} R_{i,j,t}}{\sum_{k} (\sum_{j \in k} MV_{i,j,t-1} R_{i,j,t})}.$$

The top plot presents asset weight levels for different asset classes and the bottom plot presents active weight changes for different asset classes.

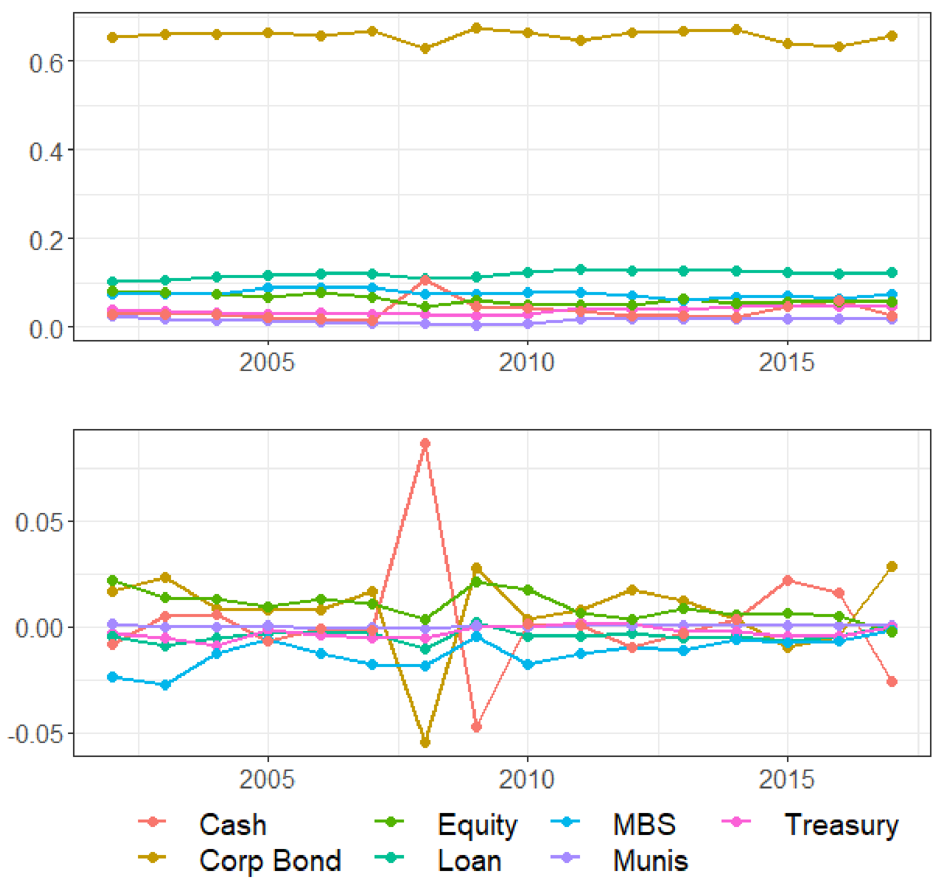


**Figure 1.6:** This figure presents the panel VAR model implied business-cash-flow shocks, valued weighted by market equity for insurers in black. The panel VAR model implied total cash-flow shocks, valued weighted by market equity for firms in the market portfolio is plotted in blue. They have a correlation of 0.64 (t-stat: 3.28).

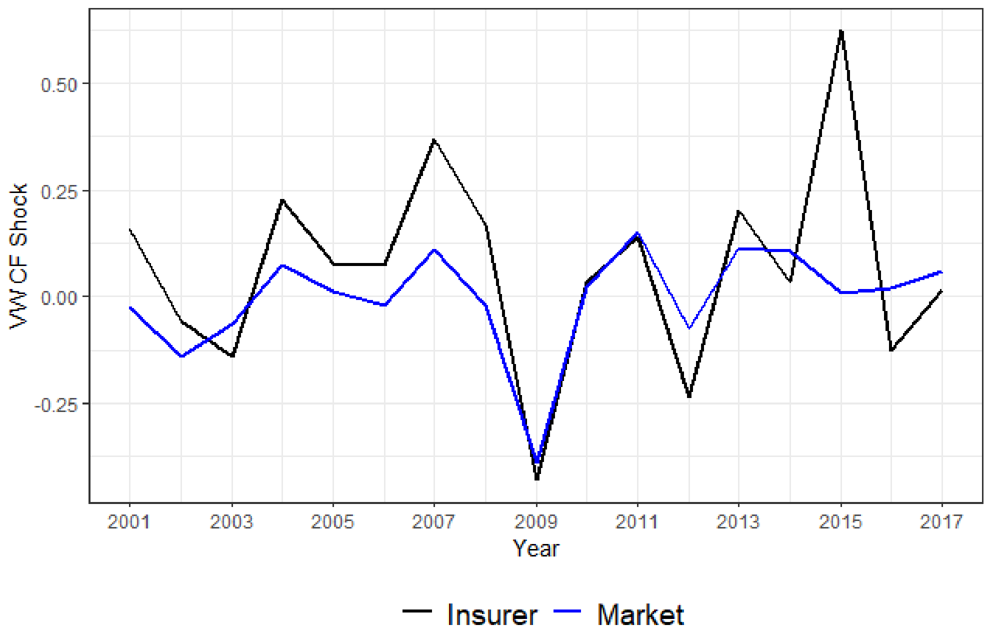



**Figure 1.7:** The plot provides the ACF estimated coefficients for net business asset dividend normalized by investment ($CF^{Bus}/E$). The blue dashed line represents a 99% confident interval.

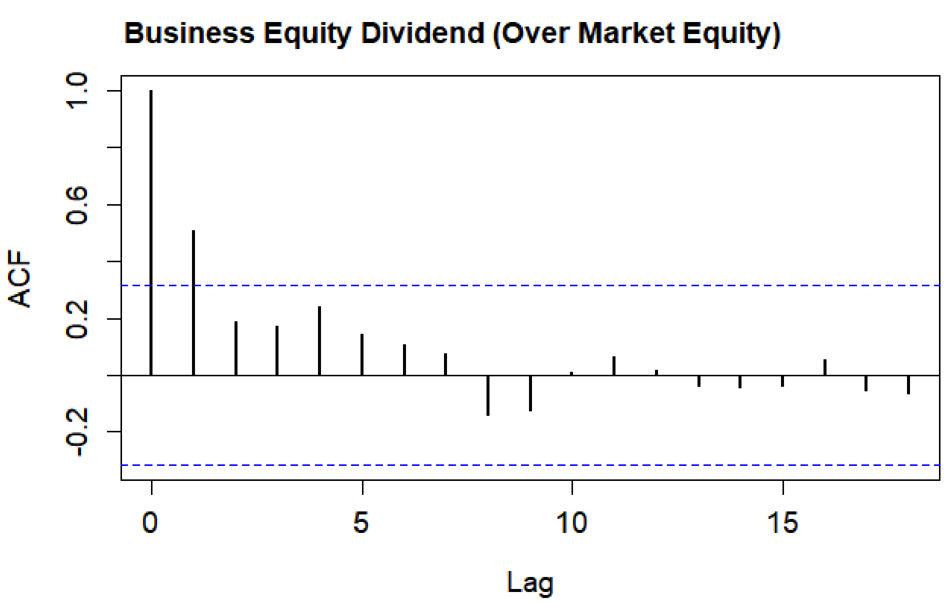


**Figure 1.8:** This figure plots the AR(1) model implied shocks for net business asset dividend (normalized by market equity, yellow) and the net business asset capital gains (blue). The correlation is 0.38 (3.29).

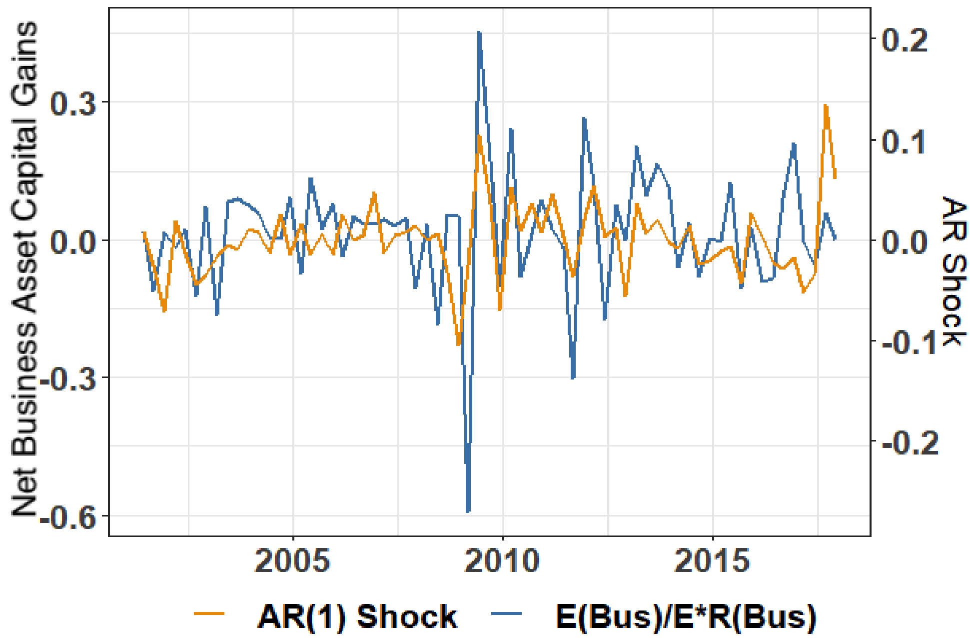



**Figure 1.9:** This figure plots the aggregate net financial asset returns for life insurance companies from 2003 to 2018. The blue line presents the net financial asset returns calculated using market value of life insurers' CUSIP level holding data. The red line presents the net financial asset returns using book equity returns (ROE) as a proxy. These two lines are highly correlated with a point estimate of 0.7 (t-stat: 6.6).

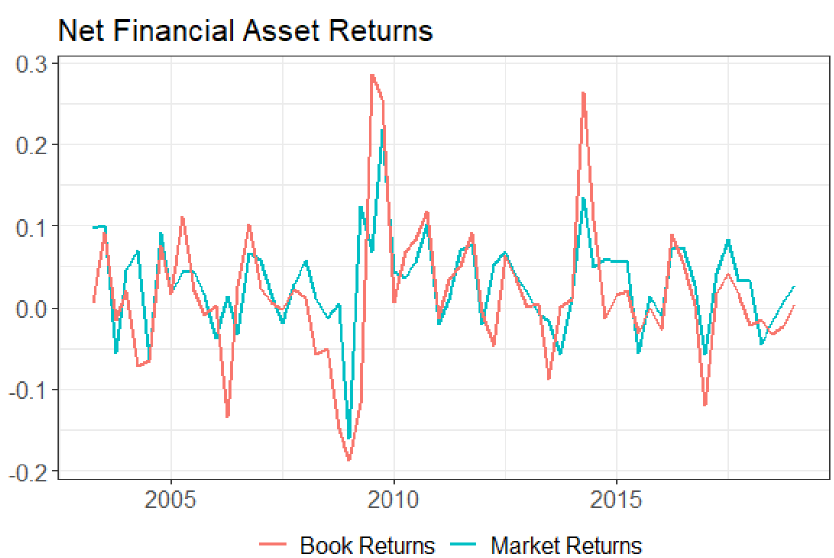


**Figure 1.10:** This figure plots the aggregate equity for financial firms. The top figures present the time series pattern of equity normalized by total assets for life insurance companies. The bottom figures present the time series pattern of equity normalized by total assets for banks. In the left plots, the pink line presents the level of the aggregate market equity, the blue line presents the level of the aggregate book equity, and the yellow line presents the differences between the aggregate market equity and book equity. In the right plots, the pink line presents the changes of market equity, the blue line presents the changes of book equity, and the yellow line presents the differences between the changes of market equity and book equity. Life insurers' book equity explains 22% of the variation in the level of their market equity, and 19% of the variation in the changes of market equity. Banks' book equity explains 14% of the variation in the level of their market equity, and 3% of the variation in the changes of market equity.

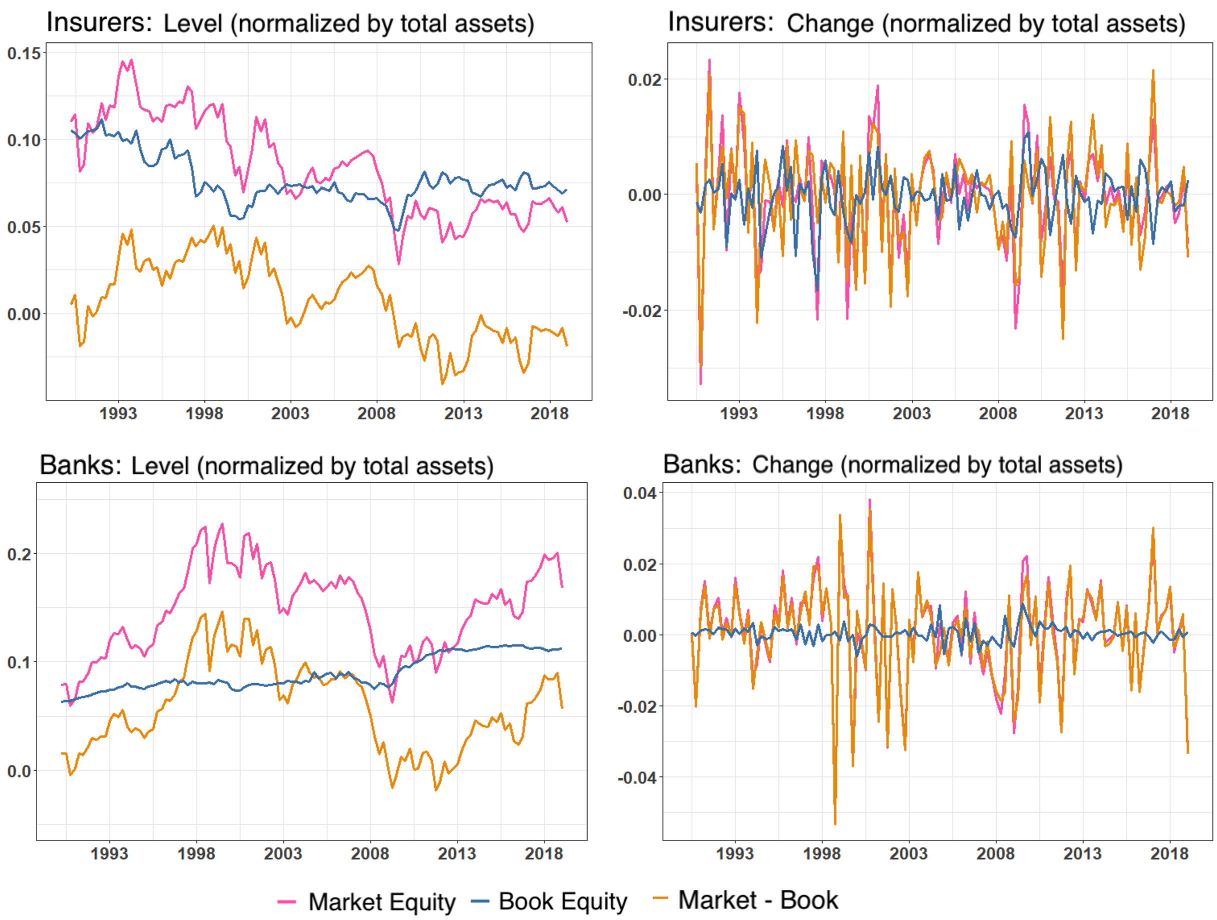


**Figure 1.11:** This figure presents the aggregate VAR model implied business-cash-flow shocks (black) and the aggregate VAR model implied total cash-flow shocks for the aggregate market portfolio (blue). The short VAR results are shown in the top figure and the long VAR results are shown in the bottom figure.

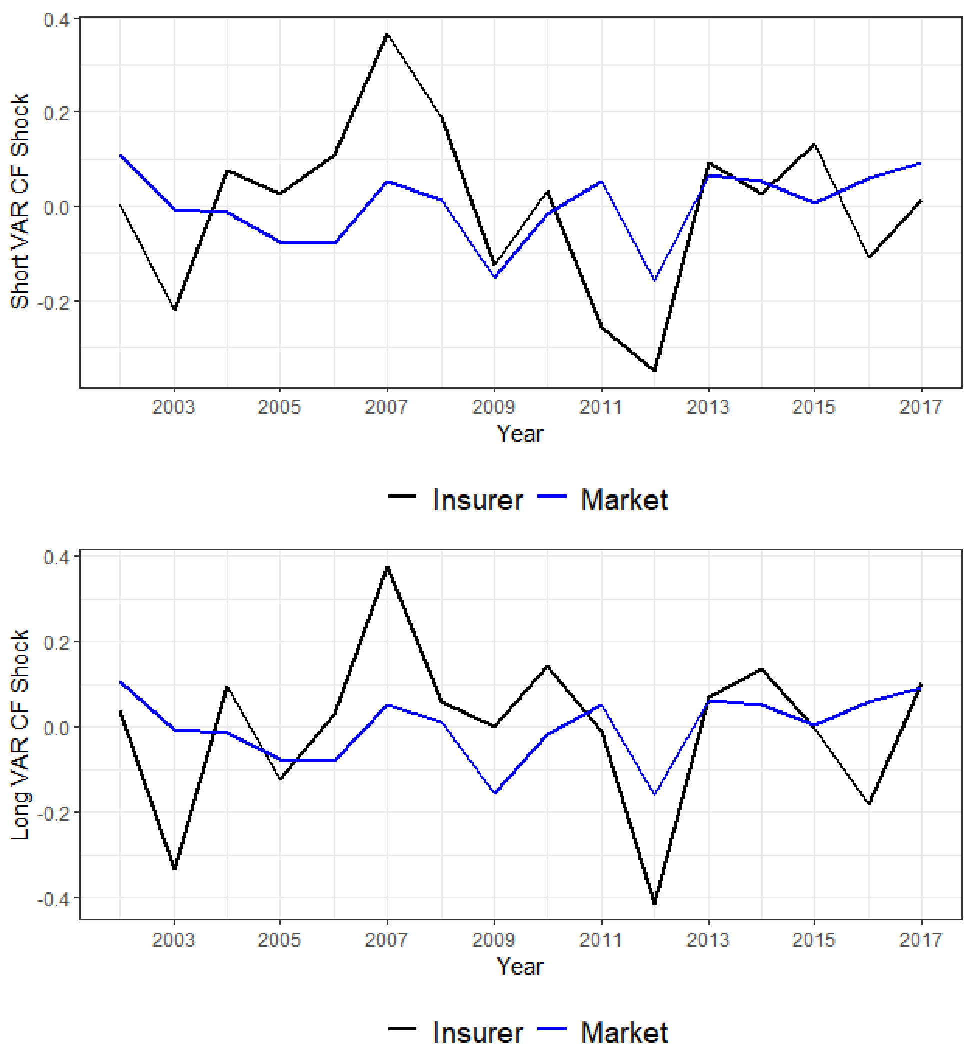


**Figure 1.12:** This figure reports the rolling aggregate 5 year cumulative business-cash-flow return for insurers (in black) and the aggregate 5 year cumulative ROE for the firms in the market portfolio (in blue). In particular, the long-term value-weighted market ROE is defined as:

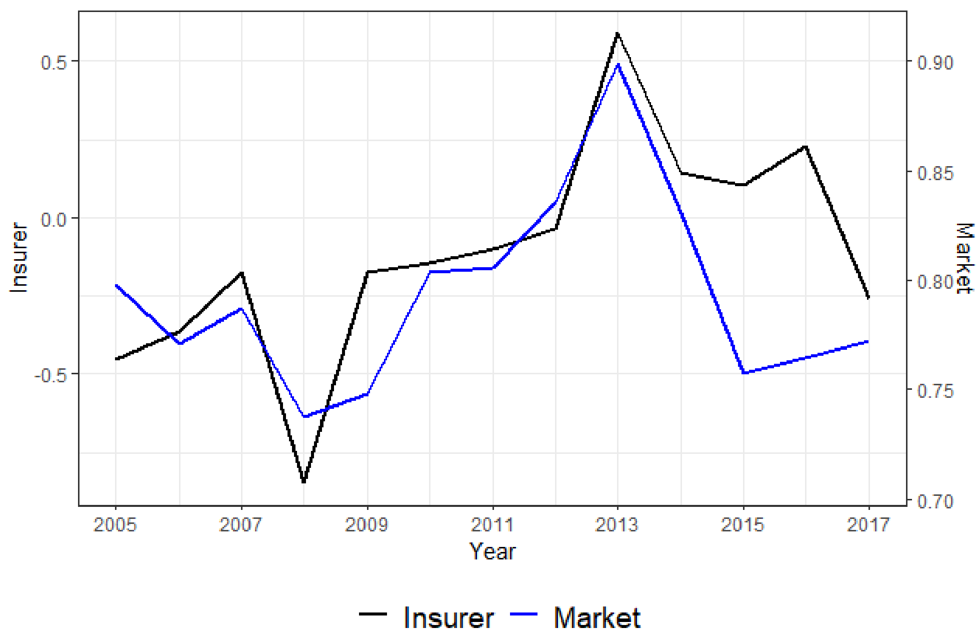
$$e_t^{M,l=5} = \frac{\sum_k E_{k,t-1}(\sum_{j=0}^{j=5} e_{k,t-j})}{\sum_k E_{k,t-1}},$$

where $e_{k,j}$ represents the log book equity return for firm $k$ at time $j$ in the market portfolio.

The long-term value-weighted business-cash-flow return for insurance companies is defined as:

$$e_t^{Bus,l=5} = \frac{\sum_{i \in I} E_{i,t-1}(\sum_{j=0}^{j=5} e_{i,t-j}^{Bus})}{\sum_{i \in I} E_{i,t-1}}$$

where $e_{i,j}^{Bus}$ represents the business-cash-flow return for insurance firm $i$ at time $j$.



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# CHAPTER 2

## Capital Reallocation

with Andrea Eisfeldt

### 2.1 Introduction

Capital reallocation is an important part of US corporate investment, representing 28% of total investment by publicly traded US firms. Moreover, capital reallocation is a direct way to reallocate assets from less productive firms to more productive firms. Accordingly, frictions impeding productive capital reallocation can exacerbate misallocation and depress aggregate productivity.

Working definitions of capital reallocation are based on measurement in models or in empirical work. For the purposes of this article, we define capital reallocation as the transfer or sale of capital between productive technologies or firms. In our stylized model, capital reallocation involves the sale of capital, $k$ from one firm or technology, associated with a particular productivity, $a_i$ and size $k_i$, to another firm with productivity $a_j$ and pre-reallocation size $k_j$. In the data, we primarily measure capital reallocation as sales of property plant and equipment, or as acquisitions of entire divisions or firms.

The focus of our review is on the role of capital reallocation in US business cycles. We aim to promote research studying the frictions which impede productive reallocation over the business cycle, as well as research into the role of capital reallocation and misallocation in determining fluctuations in aggregate productivity.

Our focus on the role of capital reallocation in US business cycles is motivated by two robust stylized facts, first documented by Eisfeldt and Rampini [2006]. First, capital reallocation is strongly and significantly procyclical. The correlation between the cyclical components of corporate capital reallocation and GDP is 0.58 in US data covering public firms from 1972 to the present, and this correlation is significant at the one percent level.

Second, the highly procyclical nature of capital reallocation stands in stark contrast to the cyclical properties of the measured benefits to capital reallocation. Measured benefits to capital reallocation are not procyclical in US corporate data. The gains to corporate capital reallocation can be computed using measures of the dispersion in the productivity of capital across firms. The cross section standard deviation of Tobin's q has no significant cyclical correlation with GDP, nor does the standard deviation of TFP growth rates across industries.[20] Furthermore, the standard deviation of capacity utilization rates across industries is significantly countercyclical.

The joint observation that capital reallocation is procyclical, while measures of dispersion in capital productivity across firms appear to be, if anything, countercyclical, lead Eisfeldt and Rampini [2006] to conclude that frictions which inhibit capital's reallocation to its best use are countercyclical. Business cycle frictions which prevent marginal products from being equated over time or in the cross section were termed business cycle wedges by Chari, Kehoe, and McGrattan [2007], and were used to explore the effects of misallocation on differences in productivities across countries by Hsieh and Klenow [2009].

This paper aims to achieve three goals, namely: (1) to review the facts and the empirical literature studying capital reallocation, (2) to relate the study of capital reallocation to modern studies of business cycles with frictions, and (3) to explore the integration of research on capital reallocation with research on misallocation and aggregate TFP. We pursue each goal with the overarching objective of providing fruitful directions for future research.

In Section 2.2 we review the empirical literature on capital reallocation and productivity dispersion. We also present a comprehensive set of stylized facts describing the cyclical properties of the amount of capital reallocation, the benefits to reallocation as measured by productivity dispersion across firms, and reallocation frictions such as financial or uncertainty shocks. In Section 2.3 we review the literature on business cycles and capital reallocation with frictions, and provide a simple model of capital reallocation in a static equilibrium

[20]See Solow [1957] and Brainard and Tobin [1968].

model of capital reallocation and production. We illustrate the role of aggregate productivity, productivity dispersion, borrowing constraints, and capital liquidity costs in determining aggregate capital reallocation. In our model, increased productivity alone does not lead to a greater quantity of capital reallocation. Improvements in financial conditions or capital liquidity increase reallocation, and the increase is greater if dispersion in productivity is large. Finally, in Section 2.4, we integrate the methods and findings from Eisfeldt and Rampini [2006] regarding capital reallocation and capital reallocation frictions with the insights from Hsieh and Klenow [2009] regarding the effects of capital misallocation on aggregate productivity. We argue that the amount of reallocation provides crucial information about capital misallocation, and reallocation frictions, in the US across booms vs. recessions. A measure of misallocation costs which uses both capital reallocation and productivity dispersion data suggests that about half of output losses in recessions are due to the lower rate of capital reallocation from less produtive to more productive firms.

## 2.2 Stylized Facts

In this section, we review the stylized facts on capital reallocation, and measures of productivity dispersion that, in a simple frictionless model, capture the benefits to capital reallocation. We briefly discuss caveats to these benefits measures. A comparison to labor reallocation is also provided. Finally, motivated by modern studies of business cycles, we discuss the relation betwen measures of capital reallocation, and measures of firm financing and finanical uncertainty.

The empirical literature on capital reallocation has documented two main facts about corporate capital transactions. First, capital reallocation appears to come in waves that coincide with either high aggregate productivity, high equity market valuations, or both. This is true for both piecemeal reallocation through sales of property, plant and equipment (see Eisfeldt and Rampini [2006]), and for mergers of entire firms (see Caballero and Hammour [2001], Jovanovic and Rousseau [2002], Harford [2005], Eisfeldt and Rampini [2006], and

Caballero [2007]).[21] Second, capital tends to flow from less productive managers, firms, or divisions to more productive ones (see Maksimovic and Phillips [1998] and Maksimovic and Phillips [2001], Schoar [2002], Giroud and Mueller [2015], David [2011], and Kehrig and Vincent [2017]).

The top panel of Table 2.1 provides data on turnover rates for sales of PP&E and acquisitions by US public companies. On average, 1.96% of capital is reallocated annually. On average, boom years, defined as years in which GDP is above its HP filtered trend, correspond to a 50% higher reallocation rate. The top panel of Table 2.1 shows that capital reallocation measured by sales of PP&E and acquisitions by US public companies is highly and statistically significantly correlated with GDP at the cyclical frequency.[22] The point estimate is 0.58 and is significant at the 1% level. Figure 2.1 plots the cyclical components of reallocation vs. GDP to visually illustrate the procyclical nature of the amount of capital reallocation.

Understanding the drivers of capital reallocation, as well as potential reallocation frictions and resulting capital misallocation, requires an understanding of the benefits to capital reallocation. Dispersion in firm-level productivity has been used to measure opportunities for productive corporate reallocation. However, we note that the extent to which measured productivity dispersion represents reallocation opportunities is an interesting and open question. The answer depends on the technologies (homogenous capital vs. putty-clay, as in Johansen [1959]), on the risk characteristics of firms (see David, Schmid, and Zeke [2018] for the effect of risk-pricing on estimates of the marginal product of capital), and on whether dispersion proxies for firm-level uncertainty or productivity differences (see Bloom [2009]).

The business cycle properties of productivity dispersion, interpreted as opportunities for productive reallocation, have been documented in two main studies. Eisfeldt and Rampini

[21]See Ottonello [2017] for the related finding that more structures are vacant following negative financial shocks.

[22]The Appendix contains the data description. Table 2.1 provides an update to Tables 1 and 3 in Eisfeldt and Rampini [2006]. The results, using sixteen additional years of data, are remarkably similar to the results in that paper.

[2006] show that dispersion in firm-level Tobin's $q$ and dispersion in firm-level investment rates have no statistically significant cyclical correlation with GDP.[23] They also show that dispersion in industry-level TFP growth rates and capacity utilization rates are countercyclical. Eisfeldt and Rampini [2006] used Compustat data, along with industry level data. A very important, and more recent, contribution to the measurement of productivity dispersion over US business cycles using establishment level data is Kehrig [2015]. Kehrig [2015] rigorously documents two key facts for the capital reallocation and resource misallocation literatures: First, dispersion in productivity levels across establishments, within industries, is countercyclical. Second, the increase in dispersion in recessions is mainly driven by a higher share of lower productivity establishments. Kehrig's study represents a very important step for understanding the effects of misallocation on aggregate TFP over US business cycles.[24] His evidence shows that, at the establishment level, the apparent benefits to capital reallocation are strongly countercyclical.

Consistent with this prior research, the bottom panel of Table 2.1, and the associated plot in Figure 2.2, illustrate that simple measures of the benefits to reallocation are not statistically significantly positively correlated with GDP at the cyclical frequency. This fact makes the procyclical nature of capital reallocation puzzling from the perspective of a frictionless neoclassical model. Firm-level dispersion in Tobin's $q$ has no significant cyclical correlation with GDP. The dispersion in TFP growth rates across industries is not significantly cyclical either. Dispersion in capacity utilization across industries is countercyclical.

In addition to studying the relationship between the amount of, and benefits to, capital reallocation and GDP at the cyclical frequency, we also report the direct correlation between the cyclical components of the amount of reallocation, and measures of the dispersion in the marginal product of capital, in the top panel of Table 2.2. The direct correlations support

[23] Jovanovic and Rousseau [2002], argues that dispersion in $q$ drives merger waves. Using Compustat data, they show that merger waves coincide with wider dispersion in firm-level Tobin's $q$. One caveat is that aggregate valuation waves can lead to very high values of Tobin's $q$ for a subset of firms. Indeed, Eisfeldt and Rampini [2006] show that excluding very large $q$'s (above five), changes the estimated correlation between the cyclical component of GDP and dispersion in $q$ from positive to negative.

[24] See also Kehrig and Vincent [2017].

the conclusions from Table 2.1. The only significant correlations, between reallocation and industry level dispersion in capacity utilization, and firm-level dispersion in pre-reallocation marginal products of capital, are negative.

For comparison, we also report the cyclical properties of labor reallocation up to the present date.[25] A comparison between labor and capital reallocation is interesting because labor and capital are likely subject to different frictions, but both labor and capital should flow from less productive firms to more productive firms to equalize marginal products. As can be seen in Panel C of Table 2.1, job creation, which is the counterpart to new investment for capital is procyclical. The direct labor counterpart to capital reallocation is excess job reallocation, or the minimum of job creation and job destruction. Excess job reallocation has no statistically significant correlation with GDP at the cyclical frequency.

Relative to the literature on labor reallocation, the literature on capital reallocation is less expansive.[26] This is striking, because most studies of the effects of financial frictions focus on constraints which limit the growth of firms' capital stocks. Moreover, capital reallocation appears to be more procyclical than either gross or excess labor reallocation. Part of the imbalance between studies of capital vs. labor reallocation may be because capital can also be "reallocated" through new investment. However, capital reallocaction is an important part of investment overall. Reallocation averaged about 28% of total investment for public US firms over our sample, which matches the finding in Eisfeldt and Rampini [2006] using data up to 2000.[27] Reallocation, or the purchase of used capital, can also be a faster way to accumulate capital than new investment. Finally, if different constraints and costs affect the reallocation of existing capital vs. the production of new capital, comparing these two types of investment can be used to identify important business cycle frictions. Finally, Lanteri [2016] presents intriguing new evidence that used capital prices are more volatile and procyclical

[25]See Davis and Haltiwanger [1992] and Davis, Haltiwanger, and Schuh [1998].

[26]See Eisfeldt and Rampini [2006] and Caballero [2007] for comparisons between capital and labor reallocation.

[27]Ramey and Shapiro [1998a] also emphasize that capital reallocation represents a sizable contribution to total US investment.

than prices of new capital.

The bottom panel of Table 2.2 reports the correlation between the cyclical components of the reallocation measures and financial flows, as well as measures of uncertainty. These financial flow and uncertainty variables are motivated by the literature on business cycles with financial frictions and uncertainty shocks.

Capital reallocation is significantly positively correlated with debt financing, and total financing, in support of theories of capital reallocation in the presence of financial frictions.[28] On the other hand, capital reallocation is not significantly correlated with equity financing.

Uncertainty measures such as the VIX and dispersion in the idiosyncratic component of stock returns do not display a significant correlation with measures of capital reallocation at the cyclical frequency. This may not be surprising, since firm-level uncertainty measures are closely related to the measures of productivity dispersion used to measure the benefits to capital reallocation. The bottom panel of Table 2.1 shows that these related reallocation benefits measures have little or no cyclical correlation with reallocation. Bloom [2009] shows that uncertainty shocks can generate realistic business cycle dynamics. Recent studies have found that the effect of uncertainty shocks may work through an interaction with financial frictions.[29]

Most existing studies of business cycles with financial frictions and uncertainty shocks focus on new investment. We explore the role of aggregate productivity shocks, financial constraints, and changes in productivity dispersion in an illustrative equilibrium model of capital *reallocation* in Section 2.3. The model confirms the empirical plausibility of important interactions between productivity dispersion and financial constraints in explaining capital reallocation dynamics.

[28] For the reasons stated in Covas and Den Haan [2011], we focus on the bottom 90% of firms as defined by total asset size. Large firms do not appear financially constrained, and are so large relative to the rest of firms that their behavior can change the cyclical properties of aggregate quantities in Compustat.

[29] See Christiano, Motto, and Rostagno [2014], Gilchrist, Sim, and Zakrajšek [2014], Arellano, Bai, and Kehoe [2016], and Alfaro, Bloom, and Lin [2016].

## 2.3 Capital Reallocation and Business Cycles: Theory

In this section, we review the theoretical literature on capital reallocation over the business cycle, and use a simple model to illustrate promising directions for future research. The literature on capital reallocation over the business cycle is closely related to, and builds on, the more general literature on business cycles with financial and real frictions. Three widely studied mechanisms used in the modern business cycle literature to generate realistic economy wide fluctuations are financial frictions, uncertainty shocks, and physical adjustment costs. We begin by reviewing the related literature, which also includes studies which incorporate realistic over-the-counter (search) models of capital reallocation. We conclude this section by presenting and analyzing a parsimonious model of equilibrium capital reallocation to illustrate the important role of three key frictions in determining capital reallocation, namely financial constraints, uncertainty or productivity dispersion, and technological or specificity costs of reallocation. We use this model to integrate lessons from the literature and to provide directions for future research.

### 2.3.1 Reallocation Theory Literature

Several recent papers study capital reallocation and provide explanations for its cyclical properties. Many of these papers build on important recent contributions in the business cycle literature that studies the amplification and propagation of business cycle shocks via frictions affecting new investment. These modern business cycle models feature either financial shocks (see Gertler and Kiyotaki [2010], Khan and Thomas [2013], Jermann and Quadrini [2012]), or shocks to the dispersion of individual firm-level productivities, (see Bloom [2009]), or both financial and uncertainty shocks (see Christiano, Motto, and Rostagno [2014], Gilchrist, Sim, and Zakrajšek [2014], Arellano, Bai, and Kehoe [2016], and Alfaro, Bloom, and Lin [2016]).

The interaction between financial frictions and capital reallocation has been explored in several recent papers. Herrera, Kolar, and Minetti [2011] provide the stylized facts for credit reallocation, and provide a link between credit reallocation and business cycles. By their measure, the reallocation of credit is highly volatile, but only moderately procyclical. Chen and Song [2013] show that the difference in capital productivities of financially constrained firms vs. unconstrained firms is higher in recessions. Their finding supports the idea that financial constraints play an important role in preventing resources from flowing to the most productive locations in recessions. Exploiting this fact in a quantitative model with TFP news shocks, the authors are able to generate realistic business cycles resulting from reallocation to financially constrained, but highly productive firms following good news about future TFP. In related work, Ai, Li, and Yang [2016] develop an extension of Gertler and Kiyotaki [2010] in which intermediaries' ability to finance productive reallocation declines following negative financial shocks. The resulting decline in reallocation amplifies and propagates the decline in intermediary net worth through the negative effect on productivity and output. The authors show that their model produces more realistic business cycle dynamics when financial shocks are included in addition to traditional TFP shocks. Cui [2017] develops a model of reallocation between incumbent and exiting firms. In that model, shocks which tighten borrowing constraints can actually prevent less productive firms from exiting because the decrease in their leverage increases their option value from remaining active by reducing debt overhang. This effect seems interesting given the emphasis on entry and exit in the larger literature on resource misallocation (see Hopenhayn [2014]).

Microfoundations for capital reallocation frictions include adverse selection, agency costs, and search. Eisfeldt [2004] provides an early model of an endogenous link between adverse selection and aggregate capital productivity. In that model, adverse selection increases in recessions due to lower investment in risky projects, leading to fewer reallocative shocks. Fuchs, Green, and Papanikolaou [2016] combine the effects of delayed asset sales and adverse selection in a model which generates endogenous capital liquidation costs. That paper uses the direct intuition that greater dispersion in productivity can exacerbate adverse selection problems to understand procyclical capital reallocation despite apparently countercyclical reallocation benefits. Li and Whited [2015] also study a model of capital reallocation with adverse selection. Like Cui [2017], they emphasize the role of entry and exit. An interesting feature of their model is that higher moments of the size distribution matter for reallocation dynamics. The joint distribution of productivity and size is also emphasized in Cooper and Schott [2013]. It is intuitive that this joint distribution should matter for reallocation dynamics, since both size and productivity determine marginal products.

Eisfeldt and Rampini [2008] motivates countercyclical reallocation frictions with endogenously cyclical agency costs. In their model, managers are more reluctant to downsize in bad times when outside options deteriorate. Their paper also provides an analytical expression for the output loss from misallocation due to managerial agency costs over the business cycle.

Given that the market for used capital, plants, divisions and firms is a decentralized one, incorporating search frictions seems like a very fruitful direction for capital reallocation research.[30] David [2011] develops a search model of mergers and acquisitions which generates aggregate productivity growth through an efficient reallocation of resources. New work by Dong, Wang, and Wen [2017] emphasizes the importance of both financial shocks and search frictions in a quantitative DSGE model that is able to match the stylized facts for capital reallocation, including the higher relative volatility for used vs. new capital prices documented by Lanteri [2016]. Moreover, Dong, Wang, and Wen [2017] show that search can explain capital unemployment, as documented by Ottonello [2017].[31] A related paper by Wright, Xiao, and Zhu [2018] develops a model of capital investment and reallocation subject to search, bargaining, and liquidity frictions, with an explicit focus on microfoundations and analytical characterizations. Cao and Shi [2014] also study capital reallocation in an equilibrium search model. They, like Cui [2017], stress the importance of firms' entry and exit decisions. Specifically, Cao and Shi [2014] emphasizes the role of procyclical firm entry

[30]Rocheteau and Weill [2011] provide a comprehensive review of the use of search models in understanding asset markets. See also Gavazza [2011].

[31]For related work on frictional markets and labor reallocation dynamics, see Chang [2011] and Zhang [2016]. Chang [2011] focuses on the interaction between sectoral shocks and firms' optimal hiring and firing decisions on labor markets' matching efficiency, while Zhang [2016] develops the important interaction between financial leverage and employment and wage decisions by firms in a model which emphasizes the importance of the extensive margin of firm entry and exit on labor reallocation.

in improving capital market liquidity, increasing used capital prices, and encouraging lower productivity firms to sell more capital in booms.

Physical adjustment costs and capital liquidity also play an important role in capital reallocation dynamics. Ramey and Shapiro [1998b] is an early contribution studying capital reallocation in the face of adjustment costs. Eisfeldt and Rampini [2006] argued that physical adjustment costs are unlikely to be countercyclical since opportunity costs of foregone output are actually higher in booms. However, Lanteri [2016] points out that despite the fact that less productive firms may have stronger incentives to downsize after negative aggregate productivity shocks, more productive firms may prefer to allocate their limited investment following such negative shocks to new capital if used capital is an imperfect substitute due to capital specificity. Lanteri's paper thus provides a plausible reconciliation for why the disincentive to grow by purchasing used capital for high productivity firms dominates the incentives to downsize of less productive firms during recessions, dampening capital reallocation in downturns.[32]

### 2.3.2 Model

We develop a one period general equilibrium model of capital reallocation in order to illustrate the role of aggregate productivity, cross sectional dispersion in firm-level productivity, financial constraints, and capital liquidity costs in determining the quantity and value of aggregate capital reallocation. Capital reallocation is driven by exogenously given ex-ante mismatches between firm-level productivity and capital. We begin with a baseline frictionless model, and then we add to this model a collateral constraint, and a technological or specificity cost of selling capital. Without frictions, marginal products of capital are equated across firms post-reallocation. In the models with financial or real trading frictions, the degree of frictions determines the remaining dispersion in marginal products post-reallocation. We study the comparative statics for the amount and value of aggregate capital reallocation,

[32]See also Eisfeldt and Rampini [2007] for a model in which firms choose between new and used capital. In that paper, used capital is preferred by financially constrained firms because it has a lower up front cost, despite higher lifetime maintenance costs.

describing how capital reallocation responds to aggregate productivity, to the tightness of the collateral constraint, to the dispersion in firm-level productivities, and to the size of the capital liquidity cost.

In this simple equilibrium model, we illustrate the fact that aggregate productivity shocks alone are unlikely to generate a realistic business cycle correlation for capital reallocation; higher aggregate productivity alone does not lead to greater capital reallocation in either a frictionless model, or a model with financial or real trading frictions. In contrast, relaxing financial constraints increases reallocation. Moreover, reallocation increases by more when constraints are relaxed when aggregate productivity is high. We also confirm the result in Eisfeldt and Rampini [2006], namely that reducing capital liquidity costs increases capital reallocation. If specificity costs are interpreted to include search or adverse selection costs, as in the literature described in Section 2.3.1, it is possible that these costs are countercyclical. Finally, we also study the effects of changes in productivity dispersion. Productivity dispersion has alternatively been used to measure the benefits to capital reallocation (Eisfeldt and Rampini [2006]) or capital misallocation (Hsieh and Klenow [2009]), and to measure uncertainty shocks (Bloom [2009]). Future work could help to disentangle the different effects of productivity dispersion. In our model, an increase in productivity dispersion counterfactually leads to more reallocation, that is, dispersion measures the benefits to productive reallocation. However, as in the business cycle literature, a higher dispersion in productivity can magnify the effects of changes in either financial constraints or capital liquidity costs in a way that appears consistent with empirical patterns.

The economy consists of a measure one of firms who are endowed with zero financial wealth and a productive technology to produce final output. Each firm is also endowed with idiosyncratic productivity $a_i$, and capital $k_i$, both of which are drawn from uncorrelated Pareto distributions.[33] Each firm $i$'s initial capital is drawn from a Pareto distribution $k_i \sim P(k_m, c)$, where $c > 1$ is the curvature parameter and $k_m$ is the lower bound for capital.

[33]To be precise, we use a Type $(I)$ distribution, for which the two specified parameters are the minimum value, and the tail decay parameter.

The probability density function for capital is $\frac{ck_m^c}{k_i^{c+1}}$. Productivity is independently assigned from a Pareto distribution $a_i \sim P(a_{agg}, f)$. The probability density function for productivity is $\frac{f a_{agg}^f}{a_i^{f+1}}$ where $a_{agg}$ is the lower bound of productivity and $f$ is the curvature parameter. The lower bound $a_{agg}$ captures the aggregate productivity level in the economy.[34] Recall that the higher is the tail decay parameter for the Pareto distribution, the lower is the amount of cross section dispersion. Thus, comparative statics over $f$ can be used to study the effects of increases or decreases in productivity dispersion. A higher $f$ will result in faster decay in the right tail of productivity levels, and thus a lower dispersion in productivity.

Firms have access to technologies to produce final goods according to $a_i \hat{k_i}^\theta$, with $0 < \theta < 1$, where, as in Eisfeldt and Rampini [2006], $\hat{k}_i$ denotes capital after capital sales or purchases, i.e. after capital reallocation has taken place. We normalize the price of the final product to be 1. Capital is traded at a marketing clearing price $P$. Each firm chooses capital sales or purchases to maximize their output according to:

$$\max_{r_i} \; a_i \hat{k_i}^\theta - P\, r_i + l_i - l_i(1 + r_l), \tag{19}$$

subject to the law of motion for capital,

$$r_i = \hat{k}_i - k_i, \tag{20}$$

where $r_i$ is positive if the firm is a net buyer of capital, and negative if it is a net seller, and the budget constraint

$$P\, r_i = l_i, \tag{21}$$

where $l_i$ denotes the funds that firms borrow to fund capital purchases. In the baseline model, we assume that firms borrow without constraints at a zero interest rate from an (unmodeled) financial intermediary ($r_l = 0$). We also assume zero discounting from the beginning of the

[34] The mean of $a_i$ increases in $a_{agg}$, while the coefficient of variation is invariant to $a_{agg}$.

period when reallocation (and loans) are chosen to the end of the period when output is produced and loans are repaid. Firms' optimization problems are unaffected by borrowing and lending in the frictionless model since the funds borrowed and loan repayments will cancel out exactly, and hence we drop the last two terms in Equation (19) and constraint (21) in most of what follows. The market clearing price $P$ ensures that net aggregate reallocation is zero:

$$\sum_i r_i = 0. \tag{22}$$

An equilibrium in this economy requires that all firms optimize according to Equations (19) to (21), and markets clear according to Equation (22). The model can be solved analytically as follows. Firms' first order condition is:

$$\hat{k}_i = (\frac{P}{\theta a_i})^{\frac{1}{\theta-1}}. \tag{23}$$

Equation (23) holds for each firm in the economy, and thus all marginal products of capital are equated to the equilibrium price in the frictionless model. Firms whose initial capital is larger than this optimal amount, i.e. those firms for which $k_i \geq (\frac{P}{\theta a_i})^{\frac{1}{\theta-1}}$, will be sellers, and firms whose initial capital is smaller than this amount will be buyers. Note that we can rewrite the marketing clearing condition in Equation (22) as:

$$\sum_i \hat{k}_i = \sum_i k_i. \tag{24}$$

This condition can be used to find the marketing clearing price of capital.[35] In particular, integrating over firm level capital stocks and productivity levels, the market clearing price of capital must satisfy the following equation:

$$\int_{a_{agg}}^{\infty} \frac{f a_{agg}^f}{a^{f+1}} \int_{k_m}^{\infty} (\frac{P}{\theta a})^{\frac{1}{\theta-1}} \frac{c k_m^c}{k^{c+1}} dk da = \int_{a_{agg}}^{\infty} \frac{f a_{agg}^f}{a^{f+1}} \int_{k_m}^{\infty} k \frac{c k_m^c}{k^{c+1}} dk da. \tag{25}$$

[35] We require $f + \frac{1}{\theta-1} > 1$ to ensure that the left hand side of Equation (24) is finite.

Simplifying, we have the following equation which determines the market clearing price:

$$\frac{f}{f+\frac{1}{\theta-1}}(\frac{P}{\theta a_{agg}})^{\frac{1}{\theta-1}} = \frac{ck_m}{c-1}. \tag{26}$$

After solving for the market clearing price, we can get the aggregate quantity of reallocation $R$, which is equal to one half of the sum of all capital sales plus all capital purchases:

$$R = \frac{1}{c-1}k_m^c(\frac{P}{\theta a_{agg}})^{\frac{1-c}{\theta-1}}\frac{f}{\frac{1-c}{\theta-1}+f}. \tag{27}$$

This yields the complete model solution.

Figure 2.3 provides an intuitive picture of the model solution. Fixing one level of firm-level productivity, this graph shows the trading regions for firms of various sizes as a function of the market clearing price of capital. Firms' initial endowment of capital is plotted along the x-axis. The y-axis plots the optimal post-reallocation firm size as a function of firms' initial capital, productivity (which is the same for all firms in the illustrative figure), and the market clearing price. The thin solid line plots the Pareto distribution of firm sizes. Recall that the higher is the decay parameter $c$, the smaller is the right tail of firm sizes. The horizontal line at $\hat{k}_i = \left(\frac{P}{\theta a_i}\right)^{\frac{1}{\theta-1}}$ plots firms' optimal post-reallocation capital stocks. Because all firms in the figure have the same level of productivity, they all choose the same post-reallocation size in the frictionless model. The 45-degree line plots capital stocks with zero reallocation. In equilibrium, firms move from the 45-degree line to the horizontal line which denotes optimal capital stocks. Firms to the left of the vertical line at $\hat{k}_i = \left(\frac{P}{\theta a_i}\right)^{\frac{1}{\theta-1}}$ have initial capital endowments which are smaller than optimal, so they are net buyers, while firms to the right of this line are net sellers.

With the full solution in hand, we can study how the amount of reallocation changes as aggregate productivity changes. In the data, reallocation is higher when aggregate productivity is higher. However, without frictions, in equilibrium the market clearing price of reallocated capital absorbs all of the effects of changes in aggregate productivity, leaving the quantity of capital reallocated unchanged. To see this, note that market clearing requires that Equation (24) holds. The optimal choice of capital after reallocation in the left hand side of this equation is weakly increasing in $\frac{a_i}{P}$ for each firm, while the right hand side is fixed. Thus, if $a_{agg}$ increases, increasing $a_i$ for all firms by the same amount, then $P$ must increase by this same amount so that the equation still holds, leaving reallocation unchanged.

Formally, we can compute comparative statics for the market clearing price of capital using Equation (26) and for the amount of reallocation using Equation (27). We present the comparative static results for the price and quantity of capital reallocation for the baseline model in the first rows of Panels A and B of Table 2.3, respectively. The Online Appendix contains the analytical details for all comparative statics. Table 2.3 shows that as aggregate productivity increases, the price of capital increases, while the amount of reallocation is unchanged. Similarly, we can get comparative statics for the capital price and the quantity of reallocation as a function of changes in the dispersion in productivity using the same conditions. We have that, as $f$ increases so that productivity dispersion decreases, that the price of capital falls and the amount of reallocation also declines. The increase in the amount of reallocation as dispersion in productivity increases is intuitive, since productivity dispersion measures the benefits to capital reallocation. Reallocation increases, absent other frictions, when the benefits to reallocation increase. The price effect is due to the fact that $f$ controls the thickness of the right tail of the productivity distribution. The resale price of capital is higher when the right tail is fatter.

Finally, we can compute the cross derivative between productivity dispersion across firms, and the level of aggregate productivity. Comparative static results for these cross derivatives appear in Table 2.4. Because aggregate productivity has no effect on the quantity of reallocation in the frictionless model, the cross derivative will also be zero. A higher aggregate shock leads to a smaller increase in the price of capital the lower is the cross sectional dispersion in productivity is. This is intuitive, because, with lower dispersion, the benefits to reallocation are smaller and so is the effect of aggregate productivity on prices. In contrast, given a countercyclical increase in productivity dispersion, the price would fall due to lower aggregate productivity, but the decline would actually be attenuated by the increase in productivity dispersion.

To generate comparative statics in line with the stylized facts describing capital reallocation in Section 2.2, we augment the baseline model with two frictions motivated by the literature on business cycles and capital reallocation with frictions, namely financial frictions and capital liquidity costs. We model the financial friction as a collateral constraint, such that firms which purchase additional capital can only borrow up to a fraction of the value of their initial capital stock. With the addition of this collateral constraint, firms' optimization problem in Equations (19) to (21) is augmented by the following collateral constraint:

$$Pr_i \leq \xi P k_i, \tag{28}$$

where $\xi \geq 0$ captures the tightness of the collateral constraint.[36] A higher value of $\xi$ corresponds to a more relaxed financial constraint.[37]

The augmented model also nests a capital liquidity cost paid by capital sellers, as in Eisfeldt and Rampini [2006]. The liquidity cost captures capital specificity, namely, the fact that when a firm sells capital only that fraction that is generally valuable to all firms receives the market clearing price. With the addition of capital liquidity costs, the law of motion for capital for each firm given in Equation (20) is replaced by:

$$\hat{k}_i = k_i + r_i - \Gamma(r_i)\mathbb{1}_{r_i<0}, \tag{29}$$

[36] Technically, we have that $l_i \leq \xi P k_i$ and $Pr_i = l_i$. However, since we have assumed a zero interest rate for intra-period loans, $l_i - l_i(1 + r_l) = 0$, and the collateral constraint can be applied reallocation itself without loss of generality.

[37] We note that whether firms can leverage only their capital, or also their output matters for the effects on capital reallocation. If firms can borrow against output, then higher productivity firms are less constrained and the equilibrium will feature higher reallocation, which is more sensitive to changes in the constraint tightness (see the Online Appendix for details). A closely related point is made by Li [2015] in the context of the effect of financial constraints on misallocation. That paper shows that misallocation is lower when firms can borrow against output vs. capital only.

which says the capital stock deployed for production ($\hat{k}_i$) equals the initial capital endowment ($k_i$) plus the amount of reallocated capital $r_i$ minus the reallocation cost ($\Gamma(r_i)$). The adjustment cost will be zero if firm $i$ is a capital buyer. To aid in analytics, the capital liquidity cost is specified such that all sellers face same marginal reallocation cost, regardless of how much capital they sell: $\Gamma(r_i) = \gamma|r_i|$, where $\gamma \geq 0$ describes how costly it is for firms to sell capital.

The first order conditions for buyers and sellers of capital are, respectively:

$$a_i\theta\hat{k}_i^{\theta-1} + \lambda_i\big(\xi k_i - (\hat{k}_i - k_i)\big) = P, \text{ and,} \tag{30}$$

$$a_i\theta\hat{k}_i^{\theta-1}(1+\gamma) = P, \tag{31}$$

where $\lambda_i$ is the Lagrangian multiplier on the collateral constraint.

Figure 2.4 illustrates firms' policy function for $\hat{k}_i$ across size $k_i$, for a fixed level of firm productivity, $a$, for the augmented model with a collateral constraint and capital liquidity cost. As can be seen in the figure, the borrowing constraint is linear in initial capital and the parameter $\xi$. It limits relatively smaller firms because they don't have much collateral to borrow against. The adjustment cost introduces an inaction region for initial capital stocks within which firms don't benefit from trading. The intuition is simple. If there is no inaction region, because sellers lose capital due to the adjustment cost, the marginal sellers would produce with less capital than marginal buyers. This is suboptimal for the marginal sellers and they would rather produce with their full initial capital endowment. Firms with more than the desired capital thus only begin to sell capital once their size implies that the proceeds from selling capital offsets the capital liquidity cost they must pay.

The model with frictions generates equilibrium dispersion in the marginal product of capital across firms. The marginal product of capital for unconstrained buyers will be $P$, and for capital sellers the marginal product is $\frac{P}{1+\gamma}$. The marginal product of capital for firms in the inaction region lies between these two values. The wedge between marginal products, and the dispersion in marginal products of capital post-reallocation, increases with the magnitude of the capital liquidity cost $\gamma$, as in Eisfeldt and Rampini [2006]. Finally, financially constrained firms have marginal products of capital higher than $P$, and the wedge depends on the tightness of the collateral constraint. As a result, dispersion in the marginal product of capital is also increasing in the tightness of the financial constraint.

As in the baseline model, the model with frictions is solved by first finding the optimal capital level for each firm for a given price of capital, then aggregating the demand and supply of capital, and finally solving for the equilibrium capital price which equates supply and demand and yields the equilibrium quantity of capital reallocation. We provide detailed solutions in the Appendix, along with formal comparative statics. We summarize the first order comparative statics in Table 2.3 for the baseline model, as well as for the augmented models with frictions. For exposition purposes, we nest each case of the augmented model as a separate case, turning only one friction on at a time. Panel A in Table 2.3 describes the response of the price of capital in each model to changes in parameters that are "improvements" to the economy, namely an increase in aggregate productivity, a reduction in productivity dispersion, a relaxation of the collateral constraint, and a reduction in the capital liquidity cost. Panel B of Table 2.3 describes the response of the quantity of capital reallocation in each model for these same parameter changes.

The first column of Table 2.3 shows that, for each model case, the market clearing price of capital is increasing in aggregate productivity, while, if all other parameters are held constant, the quantity of reallocation will remain unchanged. The intuition, arising from the market clearing condition, is the same for the augmented model as for the frictionless model. Again, the first order conditions for all model cases imply that the optimal choices of $\hat{k}_i$ are weakly increasing in $\frac{a_i}{P}$ for all firms. Thus, in order to clear the market in Equation (24), the level change in productivity must be absorbed by an increase in the capital price.

The second column shows that, for all model cases, a reduction in productivity dispersion leads to a lower capital price and less reallocation. When there is less cross section dispersion in productivity (higher $f$), the demand for reallocation is lower, and both the price of capital and the quantity of reallocation decrease.

The third column of Table 2.3 shows that both the price and quantity of reallocation increase when financial constraints are relaxed. The result is slightly different when the capital liquidity cost is reduced; the amount of reallocation increases but the price of capital actually declines. Thus, reducing either of the two capital trading frictions increases the amount of reallocation, but whether the price increases or decreases appears to depend on whether the trading "cost" is paid by buyers vs. sellers. Intuitively, if we relax the constraint on buyers, there will be more demand for capital, which will push the price up. The result is the opposite if the cost is paid by sellers. Relaxing sellers' reallocation cost will result in a greater supply of capital, and thus a lower capital price. Thus, the model illustrates the importance of the specific form of trading frictions for the results in models in which both buyers and sellers can face costs or constraints.

Finally, we present results for the cross effects between the aggregate productivity level, the dispersion in firm-level productivity, and the level of trading frictions. Recent theories of business cycles have emphasized the interaction between aggregate productivity and financial frictions, and between financial frictions and cross section dispersion in firm-level productivities (uncertainty shocks). Table 2.4 displays the cross comparative static results.

The left panel of Table 2.4 presents the cross comparative statics for aggregate productivity and the parameters describing cross section productivity dispersion, financial constraints, and capital liquidity. The sensitivity of the equilibrium price of capital increases by less for a given increase in aggregate productivity the lower the cross section dispersion in productivity is. This result holds for all models. With lower productivity dispersion, the benefits to reallocation are smaller and so is the effect of aggregate productivity on prices. On the other hand, the price of capital increases more when either financial constraints are relaxed, or capital liquidity costs are reduced, when aggregate productivity is high. There appears to be a positive multiplier on the price of capital from relaxing trading frictions when aggregate productivity is high.[38] As expected, the level of the aggregate productivity shock has no impact on the comparative statics for the quantity of reallocation in Panel B of Table 2.4. This is a direct consequence of the zero first derivative effect of aggregate productivity on the quantity of reallocation.

The right panel of Table 2.4 displays the cross comparative statics for the cross section dispersion in firm-level productivity, and trading frictions. For both the price of capital, and the quantity of capital reallocation, the effect of relaxing frictions is smaller when the cross section dispersion in productivities is smaller. This means that if the cross section dispersion in productivities is larger (a high uncertainty "shock"), then the effect of relaxing frictions will be larger. Loosening the financial constraint by a given amount will lead to a larger increase in reallocation and the price of capital when the dispersion in productivity is higher. Similarly, a given reduction in the capital liquidity cost will increase the quantity and price of reallocated capital by more when the cross section dispersion in productivity is higher. These findings are consistent with recent work that emphasizes the important interactions between dispersion in the cross section and financial or real frictions, such as in the models of Christiano, Motto, and Rostagno [2014], Gilchrist, Sim, and Zakrajšek [2014], Arellano, Bai, and Kehoe [2016], and Alfaro, Bloom, and Lin [2016].

The stylized capital reallocation model illustrates how adding financial frictions, or capital adjustment costs, can help to generate realistic patterns of capital reallocation. These frictions also change the effects of aggregate productivity shocks and uncertainty shocks, bringing the effects of those fundamental shocks more in line with the data. However, the model is very stylized. The output price is fixed at one, whereas in a fully general equilibrium model, the output price would be pinned down by market clearing and consumers' utility functions. We illustrated the role of capital illiquidity, or specificity costs, on capital sellers, while in practice buyers face installation costs as well. Another caveat is that, while the results for the quantity of reallocation appear to be robust, the results for how the price

[38]See Lanteri [2016] for related empirical results.

of capital changes with productivity dispersion depend on the shape of the productivity distribution. Our model features a Pareto productivity distribution, which provides analytical tractability, and features a fat right tail similar to that of a lognormal distribution. Many models feature lognormal productivity distributions, and Pareto distributions have been shown to fit firm size distributions. However, Kehrig [2015] documents a fat *left* tail in the productivity distribution during downturns. Using a mixture of uniform distributions, it is easy to show that an increase in dispersion in a fat left-tailed distribution leads to more reallocation, but at a lower price. Empirically, both the value and quantity of reallocation are proycyclical, so an increase in the thickness of the left tail of productivity in downturns cannot explain procyclical reallocation without other frictions. However, it seems important for future models of heterogeneous firms to incorporate the empirical findings of Kehrig [2015] regarding productivity distribution dynamics.

## 2.4 Reallocation, Misallocation, and Aggregate TFP

The study of capital reallocation, and the frictions which inhibit productivity increasing reallocation, is closely related to the important research measuring the effects of resource misallocation on aggregate TFP. Aggregate TFP is determined as a function of the joint distribution of firm-level TFP and firm size. Capital reallocation can increase aggregate TFP by increasing the efficiency of this joint distribution, i.e. by allocating more capital to more productive locations. The idea that capital reallocation can contribute to aggregate TFP fluctuations is suggested by the two main stylized facts from the literature on capital reallocation, namely that capital tends to flow from less productive managers or firms, to more productive ones, and that capital reallocation comes in waves that coincide with high aggregate productivity.

In this section, we review the developing literature on business cycles and aggregate TFP fluctuations due to capital reallocation frictions and capital misallocation. For comparison, we briefly review extensive growth literature on the effects of misallocation on aggregate

TFP. To motivate future work on the role of misallocation in US business cycles, we construct annual estimates of output losses from capital misallocation in recessions in two ways. The first method follows Eisfeldt and Rampini [2006], using data on both dispersion in firms' marginal products, and data on capital reallocation. The second method follows Hsieh and Klenow [2009], using only dispersion in firms' marginal products.

### 2.4.1 Literatures: Business Cycles and Growth

Early business cycle studies were conducted in a representative agent framework, however modern studies feature heterogeneous firms. Models with heterogeneous firms either explicitly or implicitly feature the effect of shocks and frictions on resource allocation in the cross section. However, as emphasized by Restuccia and Rogerson [2013] in their review of the misallocation literature, little is known about the relative fraction of business cycle fluctuations in aggregate TFP that can be attributed to time series variation in the efficiency of capital allocations in the cross section.

An early contribution studying the effect of misallocation on business cycle dynamics is Caballero and Hammour [1998], which shows how rent appropriation can lead to labor misallocation and sharp recessions. Gavazza [2011] studies real asset liquidity and shows that when real asset markets are thin, firms' average productivity and capacity utilizations are lower while dispersion in productivities and utilization rates are higher. Sraer and Thesmar [2017] show how to scale up estimates from carefully identified micro-econometric studies of the distortive effects of frictions on firm-level decisions to the macro economy.

Several papers focus on the role of financial frictions in generating capital misallocation in US data. Khan and Thomas [2013] develops a model in which credit shocks affecting firms' collateral constraints can lead to persistent recessions through greater capital misallocation in a model in which reallocation of capital occurs through new investment (see also the related work by Chen and Song [2013]). Ai, Li, and Yang [2016] explicitly focuses on the role of capital reallocation in driving variation in capital misallocation over the business cycle in their study of financial intermediation and capital reallocation. Buera and Moll [2015] show that what type of wedge collateral constraints generate (efficiency, investment, or labor) depends crucially on whether firms differ in terms of final goods productivity, investment costs, or recruitment costs. This is important because Chari, Kehoe, and McGrattan [2007] argue that investment wedges play a small role in business cycle fluctuations, a finding that has been interpreted as evidence against an important role for financial frictions. More recently, Kurtzman and Zeke [2017] describe the effects of misallocation due to the Federal Reserve Bank's unconventional monetary policy changing financing costs in heterogeneous way. Finally, Gilchrist, Sim, and Zakrajšek [2013] constructs a misallocation measure based on the observed dispersion in borrowing costs in the US manufacturing sector.[39]

Given the much larger size of the growth literature studying the effects of misallocation on TFP, it is useful to review that literature with a focus on lessons for understanding the role of misallocation in business cycle variation in TFP. An important recent literature in growth economics following Hsieh and Klenow [2009] argues that differences across countries in TFP can be largely accounted for by misallocation of capital in the cross section.[40] Recent reviews of this literature appear in Hopenhayn [2014], which emphasizes the role of selection, entry and exit on aggregate TFP, and provides a benchmark framework for analytical aggregation, and Buera, Kaboski, and Shin [2015], which emphasizes the interaction between selection and financial constraints on long-run growth outcomes.

The growth literature suggests that two main frictions can lead to substantial misallocation, namely, financial frictions and technological adjustment costs. Key contributions to the role of financial frictions in long run resource misallocation include quantitative theoretical studies (Buera and Shin [2013], Hopenhayn [2014]), and empirical studies (Midrigan and

[39]See also Cui and Radde [2016] for a model of financial misallocation. Whited and Zhao [2016] measure misallocation in India and China vs. the US using differences in debt to equity ratios within industries.

[40]Other key contributions documenting the effects of misallocation on TFP across countries include the following studies: Hopenhayn and Rogerson [1993] provide an early investigation of TFP losses from labor policy reallocation frictions. Restuccia and Rogerson [2008] provide a calibrated model of TFP losses from resource misallocation from distortive policies, and emphasize the importance of the joint distribution of distortions and productivity. Hsieh and Klenow [2014] show that older plants survive longer and are less productive in China and India, driving aggregate TFP lower relative to the US.

Xu [2014], Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez [Forthcoming], Li [2015]). However, two papers question the role of financial frictions in long run misallocation (Moll [2014], Hopenhayn [2014]). Moll [2014] shows that, in a long run steady state, self-financing can undo the effects of financial frictions on investment when differences in productivity are very persistent. On the other hand, financial frictions have large effects on allocations in transitions across steady states, by making transitions sluggish. Thus, Moll's study leaves the door open for financial constraints play a larger role in business cycles. Other recent studies emphasize technological adjustment costs over financial frictions. Prominent contributions include the empirical contributions by Asker, Collard-Wexler, and De Loecker [2014] and Bachmann and Bayer [2014], and the theoretical contribution by Eberly and Wang [2009]. Recent work integrates the role of technological, informational, and policy frictions (David, Hopenhayn, and Venkateswaran [2016], David and Venkateswaran [2017]).

In summary, the growth literature has identified important contributions to misallocation from policy distortions, from financial frictions, and from technological adjustment costs. The business cycle literature has made progress in incorporating these frictions into theoretical business cycle studies, however progress on measuring the quantitative contribution of misallocation is still scarce. To stimulate future research in this direction, we provide two estimates of the output loss from misallocation over US business cycles in Section 2.4.2.

### 2.4.2 Misallocation and Reallocation: Measurement

Hsieh and Klenow [2009] measure misallocation using cross section dispersion in the marginal revenue product of capital.[41] Cross section dispersion in marginal revenue products is a very intuitive measure of misallocation, since, without reallocation frictions, marginal revenue products should be equated. In the context of business cycles, however, measures of productivity dispersion are very noisy, and do not seem to exhibit strong business cycle correlations. As a result, we argue that incorporating data on capital reallocation, for which the cyclical

[41] Foster, Haltiwanger, and Syverson [2008] are the first to note the important distinction between TFP measured in quantity vs. price terms.

properties are precisely measured, is useful. Although our simple exercise is only illustrative, an analogy can be made to more formal estimation techniques for over-identified systems in which incorporating additional, more precisely measured moments, leads to more efficient estimation.

To illustrate the additional information in the amount of capital reallocation for understanding capital misallocation in the US time series, we conduct two measurement exercises. The first is based on Eisfeldt and Rampini [2006]. The basic idea is to compute what the output gain would be if the amount of capital reallocation observed in booms could be achieved in recessions. We find that bout half of output losses in recessions are due to the lower rate of capital reallocation from less produtive to more productive firms in downturns. The remaining difference is explained by higher aggregate productivity, and because, even before reallocation, the joint distribution of firm productivity and size is more efficient in booms.

To compute the loss of output in recessions from misallocation due to depressed capital reallocation, we first construct the firm-level distribution of pre-reallocation marginal products of capital, $mpk_{pre,i}$, for Compustat manufacturing firms each year from 1985 to 2015 following the procedure for estimating Solow [1957] residuals from a log-linear Cobb and Douglas [1928] production function detailed in the Appendix. We do this because we only observe the sellers of property, plant, and equipment, and the buyers in acquisitions. Thus, when computing hypothetical manufacturing output in recession years, we assume that capital is reallocated perfectly efficiently from the lowest to the highest marginal product firms.[42] Then, starting from the distribution of pre-reallocation marginal products of capital, we reallocate capital in each recession year subject to two different constraints. The first, tighter, constraint restricts the total reallocation rate to be equal to the observed reallocation rate in that year. The second, looser constraint allows reallocation to reach the average turnover rate observed in *boom* years. Since reallocation is higher on average in

[42]For evidence that capital reallocation flows from less productive firms to more productive firms, see Maksimovic and Phillips [1998] and Maksimovic and Phillips [2001], Schoar [2002], Giroud and Mueller [2015], David [2011], and Kehrig and Vincent [2017].

boom years, comparing output under these two constraints yields an estimate of how much higher output in recessions could be if the observed higher, boom-level capital reallocation could be achieved in recession years.

Specifically, each year, and under each of the two constraints, we remove capital from the lowest marginal product firms and allocate it to the highest marginal product firms until the appropriate constraint on capital reallocation is binding. That is, we begin by allocating capital to the highest marginal product firm until its marginal product is equalized to the second highest marginal product firm. We then allocate capital to both firms until their marginal products are equalized to the third highest marginal product firm. We continue until the constraint on capital reallocation is binding. We do the same thing for capital sellers. After the reallocation constraint binds, the marginal product of all capital purchasers will be equated, the marginal product of all sellers of capital will be equated to a lower value, and those firms that neither buy nor sell will have a marginal product of capital which lies between that of buyers and sellers. After reallocation, the ratio between marginal products of buyers (b) and sellers (s) is given by:

$$1 + \tau_t = \frac{mpk_b}{mpk_s} \tag{32}$$

where $\tau_t$ can be interpreted, for example, as an unfairly high interest rate on purchased capital as in Chari, Kehoe, and McGrattan [2007]. The more reallocation is allowed, the lower the implied wedge will be. Note that this wedge is very similar to the illiquidity cost in Eisfeldt and Rampini [2006], however, unlike in that model, here there is no iceberg (lost capital) cost to capital reallocation.[43]

Finally, we measure the potential output gain in recessions as the average gain over all recession years from increasing reallocation to the average boom turnover rate. We compute

$$\frac{E[Y(R_{\text{boom}})|_{\text{GDP} < \text{trend}}]}{E[Y(R_{\text{rec}})|_{\text{GDP} < \text{trend}}]} - 1, \tag{33}$$

[43] See Samuelson [1954] for a model with iceberg costs of trade in goods.

where $Y(R_{\text{boom}})$ and $Y(R_{\text{rec}})$ indicate that firm-level output is computed using post-reallocation capital under the boom and recession reallocation constraints respectively, and aggregate output is the sum over all firms' Cobb Douglas production functions. This calculation yields a potential manufacturing output gain in recession years of 9.08%. Of course, our assumption of efficient reallocation implies that this is an upper bound on misallocation losses in recessions relative to booms. Thus, to put the potential output gain from higher capital reallocation in perspective using an apples to apples comparison, we also compute output in both booms and recessions assuming efficient reallocation. We have

$$\frac{E[Y(R_{\text{boom}})|_{\text{GDP > trend}}}{E[Y(R_{\text{rec}})|_{\text{GDP < trend}}]} - 1 = 17.01\%. \tag{34}$$

Relative to the gain computed using Equation (33), this gain includes the potential effects of both higher reallocation in booms, and the effect from a higher mean productivity and a possibly more efficient ex-ante joint distribution of firm productivity and capital in booms. Comparing the 9.08% gain from higher reallocation alone to the full 17.01% difference in efficient-reallocation output indicates that about *half* of the output difference comes soley from the higher amount of reallocation in booms.

For comparison, we apply the method in Hsieh and Klenow [2009] to data on US public manufacturing firms over the business cycle. We refer readers to that paper for all estimation equations. We compute the efficiency loss from misallocation at each date using Equation (15) in Hsieh and Klenow [2009] and the associated Online Errata.[44] The efficiency loss from misallocation is the ratio between the hypothetical output generated if all firms were able to equalize their marginal products of capital ($Y_{\text{eff}}$), and actual output ($Y$), or $Y_{\text{eff}}/Y - 1$. Thus, this misallocation measure is a transformation of the dispersion in firms' marginal products.

On average, for US publicly traded manufacturing firms, we find that the estimated average efficiency gain is 21.24%, which is close to, but slightly smaller than, the estimate using US Census data reported in Hsieh and Klenow [2009]. The average efficiency gain in

[44] See `http://klenow.com/MMTFPAppendix.pdf`

boom years is 21.34% and in recession years it is 21.14%. The efficiency gain time series has no significant cyclical correlation with GDP. These results seem to imply that misallocation does not contribute significantly to output losses in recessions. However, this finding is unsurprising, given that the dispersion measures discussed in Section 2.2 are closely related to the efficiency gain measure, and those measures also display no significant correlation with GDP at the cyclical frequency. More precise measurement of TFP dispersion, as in Kehrig [2015], which finds countercyclical TFP dispersion using Census data, may help to uncover the true loss from misallocation using this method.

In summary, we argue that incorporating flow data on capital reallocation can help to measure misallocation frictions. Quantity data on flows is model-free, and the amount of reallocation is likely indicative of the cost. Reallocation may also be more precisely measured than marginal products of capital. On the other hand, more work needs to be done to incorporate reallocation data into measures of the aggregate misallocation loss in TFP that can be computed analytically, or that do not rely on the assumption that all reallocation is efficient.

## 2.5 Conclusion

Capital reallocation represents 28% of total investment, and about 2% of firms total assets are reallocated annually. Reallocation of corporate capital varies substantially over the business cycle, with about 50% more reallocation taking place in booms vs. recessions. Capital reallocation is highly procyclical despite the fact that simple measures of the benefits to capital reallocation do not display significant business cycle correlations.

Some progress has been made in understanding the drivers of capital reallocation over the business cycle, and the frictions which appear to inhibit reallocation in downturns. Explanations include financial frictions, adverse selection, search and technological constraints. In a simple static equilibrium model of capital reallocation, we show that financial frictions and capital liquidity costs are useful in generating variation in capital reallocation. Our model also shows that the effects of both of these reallocation frictions are amplified when productivity dispersion is higher. In this model, greater productivity dispersion robustly increases the quantity of reallocation, however the effect on the price of used capital depends on whether the right or left tail of the distribution drives dispersion. Similarly, whether buyers or sellers pay the costs of reallocation determines whether relaxed constraints or lower costs lead to higher prices, or lower prices. Future work can help to disentangle what changes in reallocation frictions and productivity dispersion are most consistent with empirical observations.

Finally, we explore the implications of lower capital reallocation in recessions for capital misallocation and associated output losses. A measure incorporating both dispersion in firms' marginal products of capital, and the amount of reallocation in booms and recessions, suggests that the greater misallocation of capital in recessions due to lower capital reallocation can lead to average output losses in recessions of 8%.

## 2.6 Appendix

### 2.6.1 Data Description

This section provides a brief description of the data we use in our study. The Online Appendix Eisfeldt and Shi [2017] contains further details, along with a link to data and codes used in this paper. For the Hodrick and Prescott [1997] filter, we use an annual parameter, equal to 100. Annual GDP data is from the FRED database from 1963-2016. Capital reallocation variables and market value weighted Tobin's $q$ are computed using the method in Eisfeldt and Rampini [2006] and Compustat data from 1971-2016 for reallocation, and 1963-2016 for Tobin's $q$. Capital and reallocation series are deflated using annual CPI data for all urban consumers are from the Bureau of Labor Statistics, and turnover rates use lagged total assets in the denominator. Total investment is the sum of capital realloation and capital expenditures. Annual gross job creation and annual gross job destruction are from Census data for 1977-2015. Excess job reallocation is job reallocation (sum of creation and destruction) minus the absolute value of the net change in employment. See Davis and Haltiwanger [1992]. For manufacturing industries, the (output-weighted) standard deviation of total factor productivity growth rates and capacity utilization across industries at the three digit NAICS code level is computed using data from the Bureau of Labor Statistics (for multifactor productivity and the value of sectoral production) and the Federal Reserve Board (for capacity utilization) covering the period 1988-2015. Financing Variables are defined following Eisfeldt and Muir [2016]. VIX is the CBOE S&P 500 Volatility Index from 1990-2016. The uncertainty shock estimation follows Gilchrist, Sim, and Zakrajšek [2014] using CRSP data 1971-2016.

### 2.6.2 Misallocation Production Function Estimation

We construct annual estimates of firm-level marginal products of capital using firm-level Compustat data on publicly traded manufacturing firms from 1985-2015.[45] We assume that each firm $i$ at time $t$ produces output using capital and labor in a Cobb-Douglas production function:

$$y_{i,t} = a_{i,t} k_{i,t}^{\alpha_i} n_{i,t}^{\beta_i}, \tag{35}$$

where $k_{i,t}$ and $n_{i,t}$ are capital and labor respectively, $\alpha_i$ and $\beta_i$ are constant firm-level capital and labor shares, and $a_{i,t}$ is the productivity level of the firm. We use sales to measure output, PP&E to measure capital, and employees times wages to measure labor. Because wage coverage is limited in Compustat data, we use six-digit NAICS industry wage data from the Census distributed by the NBER. To study business cycles, we allow firms to have different expected productivities in boom years and recession years, defined by HP filtered GDP relative to trend. We run the following time series regression for each public manufacturing firm to estimate firm-level Solow residuals:

$$\log y_{i,t} = c_i + \psi_i d_t + \alpha_i \log k_{i,t} + \beta_i \log n_{i,t} + \epsilon_{i,t}, \tag{36}$$

where the dummy variable $d_t$ is set to be 1 if $t$ is a boom year, and 0 if $t$ is a recession year, as defined by HP filtered GDP relative to trend.[46] We get TFP for each firm-year by collecting

[45] Historical NAICS codes, which we use for industry-level wage data, become available in Compustat in 1985.

[46] Firms with $\alpha_i$ or $\beta_i$ less than 0 or greater than 1 are dropped to ensure decreasing returns to scale in capital and labor for production.

the estimated intercept, dummy and residual terms from the regression in Equation (36).[47]

$$a_{i,t} = \exp(c_i + \psi_i d_t + \epsilon_{i,t}). \tag{37}$$

We then calculate the ex-ante, prior to reallocation, marginal product of capital as:

$$mpk_{pre,i,t} = a_{i,t}\alpha_i k_{i,t-1}^{\alpha_i-1} n_{i,t}^{\beta_i} \tag{38}$$

where $k_{i,t-1}$ is the beginning of the period, pre-reallocation capital stock of firm $i$. This procedure yields a panel of marginal products with 19,627 firm-year observations.[48] The median capital share estimate $\alpha$ is 0.32, and the median labor share estimate $\beta$ is 0.58.

To apply the method in Hsieh and Klenow [2009] to data on US public manufacturing firms over the business cycle requires estimates of capital and labor share parameters. For production function parameter estimates, we use the output weighted $\alpha_s = \sum \frac{Y_i}{Y_s}\alpha_i$ for each 3 digit NAICS manufacturing industry $s$, where $\alpha_i$ is from the estimate in Equation (36). Labor share is $(1 - \alpha_s)$. As in Hsieh and Klenow [2009] we use industry level wage data (3 digit NAICS industry wage data from the Census, distributed by the NBER) and firm-level data on number of employees to measure the labor input. We measure capital as the average of beginning and end of period PP&E, and we use number of employees to measure the quantity of labor.

[47] In related measurement exercises, Chen and Song [2013] and Ai, Li, and Yang [2016] use the ratio of Operating Income before Depreciation to one-year-lag net Plant, Property and Equipment to measure capital productivity.

[48] To alleviate the effect of outliers, we winsorize $a_{i,t}$ for each year at the 5% and 95% percentiles, and we drop firms with ex-ante marginal products of capital in the top and bottom 1%. We trim, rather than winsorize the marginal products to alleviate the effect of the skewed firm size distribution, which can generate extreme estimates of marginal products for large firms.

# Figures

**Figure 2.1:** Capital reallocation is procyclical. This figure plots the cyclical components of the turnover rates for capital reallocation, along with the cyclical component of GDP. Series are HP filtered to extract the business cycle component, and normalized by the respective standard deviations of the HP filtered series.

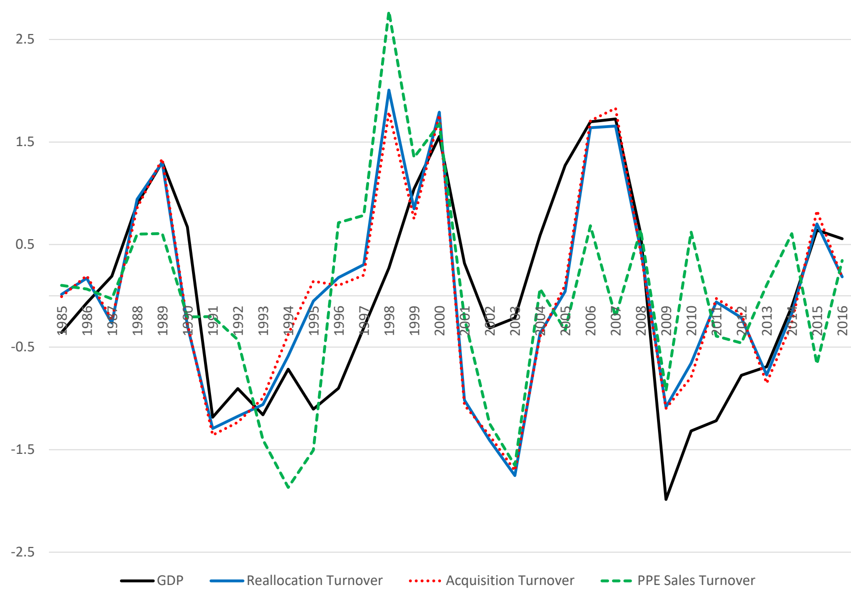


**Figure 2.2:** Productivity dispersion measures are acyclical. This figure plots the cyclical components of several measures of the benefits to capital reallocation, along with the cyclical component of GDP. Series are HP filtered to extract the business cycle component. Series are normalized by the respective standard deviations of the HP filtered series.

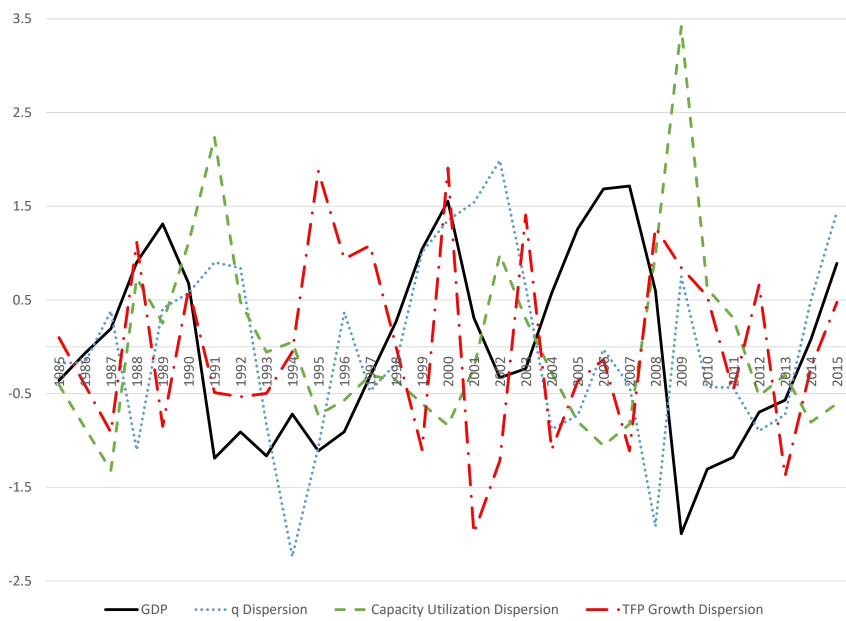


**Figure 2.3:** Trading Regions for a Fixed Level of Productivity: Frictionless Model

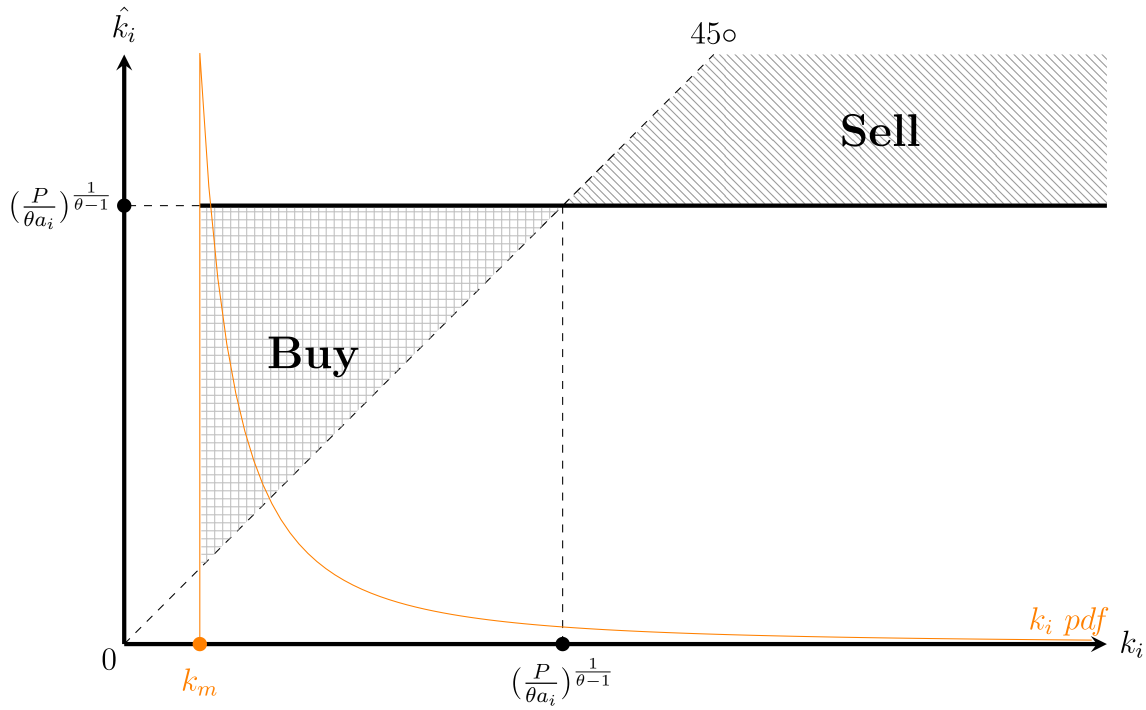
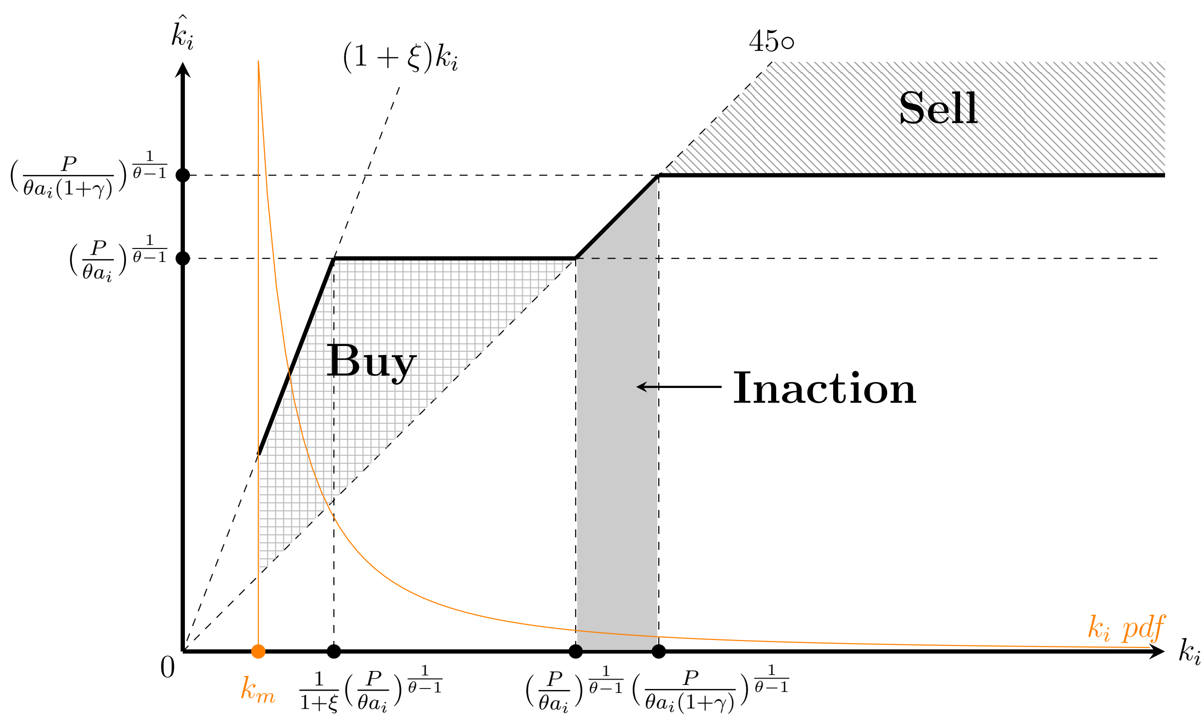



**Figure 2.4:** Trading Regions for a Fixed Level of Productivity: Model with Frictions



# Tables

**Table 2.1:** Deviations from trend are computed using an annual Hodrick and Prescott [1997] filter. Standard errors are corrected using GMM, correcting for heteroscedasticity and autocorrelation of the residuals according to Newey and West [1987]. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. Statistical significance for differences in boom and recession means is indicated next to the reported boom mean. See the Appendix for a detailed data description.

| | Correlation with GDP | Unconditional Mean | Boom Mean | Recession Mean |
|---|---|---|---|---|
| *Panel A: Capital Reallocation Turnover Rate* | | | | |
| Total Reallocation Turnover | 0.5752*** | 1.96% | 2.30%*** | 1.61% |
| | (0.1454) | | | |
| Sales of Property, Plant and Equipment Turnover | 0.3455* | 0.40% | 0.43%** | 0.36% |
| | (0.1680) | | | |
| Acquisition Turnover | 0.5861*** | 1.56% | 1.87%*** | 1.25% |
| | (0.1413) | | | |
| *Panel B: Benefits to Reallocation* | | | | |
| Standard deviation of Tobin's $q$ (firm level, $0 \leq q \leq 5$) | -0.0580 | 0.77 | 0.77 | 0.77 |
| | (0.2250) | | | |
| Standard deviation of TFP growth rates (3 digit NAICS level) | -0.1463 | 3.79 | 3.56 | 3.99 |
| | (0.3003) | | | |
| Standard deviation of capacity utilization (3 digit NAICS level) | -0.4948*** | 5.20 | 4.69 | 5.64 |
| | (0.1650) | | | |
| *Panel C: Labor Reallocation* | | | | |
| Job Creation Rate | 0.6180*** | 16.69% | 17.65% | 15.68% |
| | (0.1540) | | | |
| Job Destruction Rate | -0.3760 | 14.71% | 14.51% | 14.93% |
| | (0.2391) | | | |
| Excess Job Reallocation Rate | -0.1030 | 14.42% | 14.51% | 14.32% |
| | (0.3153) | | | |

**Table 2.2:** Deviations from trend are computed using an annual Hodrick and Prescott [1997] filter. (F) denotes firm level, (I) denotes industry level. Standard errors are corrected using GMM, correcting for heteroscedasticity and autocorrelation of the residuals according to Newey and West [1987]. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. See the Appendix for a detailed data description.

| | Total Reallocation Turnover | Sales of PPE Turnover | Acquisition Turnover |
|---|---|---|---|
| *Panel A: Correlation with Benefit to Reallocation* | | | |
| Standard deviation of | -0.0732 | 0.1464 | -0.0922 |
| Tobin's $q$ (F) $(0 \leq q \leq 5)$ | (0.2454) | (0.2951) | (0.2363) |
| Standard deviation of | 0.1437 | 0.0261 | 0.1488 |
| TFP growth rates (I) | (0.3416) | (0.3047) | (0.3490) |
| Standard deviation of | -0.5646*** | -0.2920 | -0.5778*** |
| capacity utilization (I) | (0.1218) | (0.1647) | (0.1207) |
| *Panel B: Correlation with Financial Variables* | | | |
| Debt Financing | 0.6590*** | 0.4507* | 0.6581*** |
| | (0.1530) | (0.2205) | (0.1526) |
| Equity Financing | -0.1661 | 0.0766 | -0.1876 |
| | (0.4199) | (0.3439) | (0.4180) |
| Total Financing | 0.5261** | 0.4768** | 0.5122** |
| | (0.2114) | (0.2029) | (0.2144) |
| VIX | -0.0691 | 0.2176 | -0.1082 |
| | (0.3377) | (0.2913) | (0.3287) |
| Uncertainty Shock | 0.1744 | 0.3433 | 0.1518 |
| | (0.3183) | (0.2194) | (0.3247) |

**Table 2.3:** Comparative Statics: Capital Price and Quantity of Reallocation

| | Agg Shock ($a_{agg} \uparrow$) | Productivity Dispersion ($f \uparrow$, disp. $\downarrow$) | Financial Shock ($\xi \uparrow$) | Liquidity Shock ($\gamma \downarrow$) |
|---|---|---|---|---|
| *Panel A: Capital Price Sensitivity* | | | | |
| Baseline Model | $+$ | $-$ | | |
| Collateral Constraint | $+$ | $-$ | $+$ | |
| Liquidity Cost | $+$ | $-$ | | $-$ |
| *Panel B: Reallocation Sensitivity* | | | | |
| Baseline Model | 0 | $-$ | | |
| Collateral Constraint | 0 | $-$ | $+$ | |
| Liquidity Cost | 0 | $-$ | | $+$ |

**Table 2.4:** Cross Comparative Statics: Capital Price and Quantity of Reallocation

| | Agg Shock ($a_{agg} \uparrow$) | | | Productivity Dispersion ($\beta \uparrow$, disp. $\downarrow$) | |
|---|---|---|---|---|---|
| *Panel A: Capital Price* | $\partial P/\partial f$ | $\partial P/\partial \xi$ | $\partial P/\partial \gamma$ | $\partial P/\partial \xi$ | $\partial P/\partial \gamma$ |
| Baseline Model | $-$ | | | | |
| Collateral Constraint | $-$ | $+$ | | $-$ | |
| Liquidity Cost | $-$ | | $+$ | | $-$ |
| *Panel B: Reallocation* | $\partial R/\partial f$ | $\partial R/\partial \xi$ | $\partial R/\partial \gamma$ | $\partial R/\partial \xi$ | $\partial R/\partial \gamma$ |
| Baseline Model | 0 | | | | |
| Collateral Constraint | 0 | 0 | | $-$ | |
| Liquidity Cost | 0 | | 0 | | $-$ |

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