Financial Constraints and Moral Hazard: The Case of Franchising*

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Abstract

Financial constraints are an important impediment to the growth of small businesses. We study theoretically and empirically how the financial constraints of agents affect their decisions to exert effort, and, hence the organizational decisions and growth of principals, in the context of franchising. We find that a 30 percent decrease in average collateralizable housing wealth in a region delays chains' entry into franchising by 0.28 years on average, 9 percent of the average waiting time, and slows their growth by around 10 percent, leading to a 10 percent reduction in franchised chain employment.

Keywords: Contracting, incentives, principal-agent, empirical, collateralizable housing wealth, entry, growth

JEL: L14, L22, D22, D82, L8

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1 Introduction

The recent Great Recession led to a sizable deterioration in households' balance sheets. The resulting decline in households' collateralizable wealth has been suggested as a major factor adversely affecting the viability and growth of small businesses. For example, in their report for the Cleveland Fed, Schweitzer and Shane (2010) write "(we) find that homes do constitute an important source of capital for small business owners and that the impact of the recent decline in housing prices is significant enough to be a real constraint on small business finances." This empirical observation is consistent with the well-known importance of collateral for the credit market. By requiring a debt contract to be collateralized, banks mitigate the moral hazard problem of an entrepreneur who otherwise engages in too little effort due to the possibility of default (see, for example, Bester (1987)). A decline in households' collateralizable wealth thus can lead to credit rationing and hence affect the creation and growth of small business adversely. Such moral hazard problem is even more acute in franchising, where the main purpose of the franchise relationship is to induce higher effort from a franchisee than from a salaried manager.[1] Because of the importance of moral hazard on effort, franchisors – even established ones with easy access to capital markets – normally require that their franchisees put forth significant portions of the capital needed to open a franchise. Franchisors view this requirement as ensuring that franchisees have "skin in the game."

In this paper we study theoretically and empirically how the financial constraints of agents affect the organizational decisions and growth of principals in the context of franchising. How much collateral an agent can post may affect her incentives to work hard because higher collateral leads to a lower repayment, which implies a lower probability of default and hence greater returns to her effort. An agent's financial constraints thus affect the principal's interests in engaging in the relationship, i.e., the principal's organizational decisions. We view franchising as an ideal context to study the issue of agents' financial constraints and moral hazard, and their impact on principals' organizational decisions and eventually growth, for several reasons. First, through their initial decision to begin franchising and their marginal decisions on whether to open a new outlet as a franchisee- or company-owned outlet, we obtain many observations regarding organizational choice, i.e., the choice between vertical separation (franchising) and integration (company-ownership). Second, industry participants recognize the impact of franchisee financial constraints and express concern about this (see for example Reuteman (2009) and Needleman (2011)). Third, franchised businesses are an economically important subgroup of small businesses. According to the Economic Census, franchised businesses accounted for 453,326 establishments and nearly $1.3 trillion in sales in 2007. They employed 7.9 million workers, or about 5% of the total workforce in the U.S.

[1] A franchised establishment carries the brand of a chain and conforms to a common format of the products or services offered. However, the outlet is owned by a franchisee, who is a typical small entrepreneur, i.e., an individual (or a household) who bears the investment costs and earns the profit of the establishment, after paying royalties and other fees to the chain, also known as the franchisor.

To guide our empirical analyses of the impact of households' collateralizable wealth on franchisors' organizational form decisions, we set up a simple principal-agent model where franchisee effort and the profitability of franchised outlets depend on how much collateral a franchisee is able to put up. In the model, the franchisee signs two contracts, namely, a debt contract with a bank, so she can finance the required capital, and a franchise contract with her franchisor. After committing to these, the franchisee decides on effort. Revenue is then realized, at which point she decides whether or not to default on the debt contract. A higher level of collateral implies lower probability of defaulting and higher returns to effort, and hence a greater incentive to choose high effort. The franchisor's problem is to choose whether to open an outlet and if so, via what organizational form, when an opportunity for opening an outlet arrives. In the model's equilibrium, the expected profit generated by a franchised outlet for the chain is increasing in the average collateral of potential franchisees as well as other factors such as the number of potential franchisees and the importance of franchisee effort in the business.

We use the above findings to guide our empirical model, which describes the timing of chains' entry into franchising – an aspect of the franchisors' decision process that has not been looked at in the literature – and their growth decisions pre and post entry into franchising. Using data from 934 chains that started their business and subsequently started franchising some time between 1984 and 2006, we estimate the determinants of these decisions. We combine our chain-level data with other information about local macroeconomic conditions. In particular, we use collateralizable housing wealth, measured at the state level, to capture the average financial resources of potential franchisees in each state. Collateralizable housing wealth can have an effect on the opening of franchised outlets not only through the incentive channel we discussed above but also through its effect on aggregate demand. We can separately identify the impact of the incentive channel because we observe two growth paths, the growth path in the number of company-owned outlets and the growth path in the number of franchised outlets. The variation in the relative growth of the number of franchised outlets helps us identify the effect of collateralizable housing wealth via the incentive channel, while the variation in the overall growth of a chain allows us to control for the potential effect of collateralizable housing wealth via the demand channel.

The estimation results we obtain are consistent with the implications of our simple principal-agent model of franchising. In particular, we find that collateralizable housing wealth has a positive effect on the value of opening a franchised outlet relative to opening a company-owned outlet. This accords with the intuition that franchisees who can put more collateral down to start their business have greater incentives to work hard. As a result, the profitability of franchising to franchisors increases. Conversely, and consistent with the same intuition, we find that both the amount of capital required to open an outlet and the interest rate have a negative effect on the value of franchising. In addition, we find that the interaction of the number of employees needed in the business and collateralizable housing wealth has a positive impact on the value of franchising.

Since hiring and managing labor are a major part of what local managers do in the types of businesses where franchising occurs, these larger effects for more labor-intensive businesses are consistent with the idea that franchisee incentives arising from having more collateral at stake are particularly valuable in businesses where the manager's role is more important to the success of the business. This again demonstrates the incentive channel through which potential franchisees' financial constraints affect the franchisors' growth.[2]

To understand the magnitude of the effect of franchisees' financial constraints on franchisors' decisions, we simulate the effect of a 30 percent decrease in the collateralizable housing wealth of potential franchisees, a change consistent with the decline in housing values during the recent Great Recession. We find that chains enter into franchising later, and open fewer franchised outlets and, more importantly from a job creation perspective, fewer total outlets. Specifically, we find that chains on average delay entry into franchising by 0.28 years, 9% of the average waiting time. The number of total outlets of chains five years after they start their business decreases, on average, by 2.43 or 10.11%. The average decrease in the number of total outlets ten years after a chain starts its business is 4.29 or 10.27%. Combined with Census Bureau information about the importance of (business-format) franchising in the U.S. economy, our results suggest that such a 30 percent decrease in collateralizable housing wealth for franchisees could affect as many as 650,000 jobs.

By studying the effect of agents' financial constraints on principals' organizational form decisions and growth, this paper contributes to the empirical literature on contracting and contract theory. There is relatively little empirical work on contracting compared to the large amount of theoretical research in this area. Moreover, much of the empirical literature focuses on the role of residual claims and regresses contract types, or the relative use of one contract type versus the other, on principal and agent characteristics (e.g., Brickley and Dark (1987), Lafontaine (1992), Laffont and Matoussi (1995), Ackerberg and Botticini (2002), Dubois (2002) and Lafontaine and Shaw (2005). Chiappori and Salanié (2003) provide a survey of recent empirical work on testing contract theory while Lafontaine and Slade (2007) survey the empirical literature on franchising.) In the present paper, we instead study the effect of agents' financial constraints on principals' organizational form decisions, growth and timing of entry into franchising.[3] We view the incentive effect of

[2]Note that the results concerning the direct effect of collateralizable wealth on the growth in number of franchised outlets are consistent also with the idea that franchisors may choose the franchising format to overcome their own financing constraints. However, there are reasons to expect that this explanation for franchising is at least incomplete since franchisors could obtain financing at cheaper rates if they sold shares in portfolios of outlets rather than selling individual outlets. The latter becomes a source for lower-cost capital only when combined with expected effort exerted by the owner of an outlet, i.e., only when franchisors recognize that a franchisee is not just an investor (see Lafontaine (1992) for more on this.) Moreover, the positive interaction effect for collateralizable wealth and number of employees needed is consistent with the implications of our model but is not predicted by the franchisor financial constraint argument.

[3]Laffont and Matoussi (1995) is the only paper in the literature which we are aware of that also studies the role of agents' financial constraints. In their model, when the tenant for a piece of land is financially constrained, it is impossible for her to sign a contract that offers a high share of output because such contracts also require a high upfront rental fee. In our context, franchisee wealth is used as a collateral, and the amount of collateral serves as an

collateralizable wealth as complementary to that of the residual claims or incentive compensation that are the typical focus of the agency literature. This is because collateralizable wealth gives incentives to franchisees in the early years of operation for their business, a period during which profits, and hence residual claims, are often negative but the amount of wealth put up in the business is at its maximum.

This paper is also related to an emerging literature in macroeconomics on deleveraging, which considers how a decline in home equity can lead to a recession (e.g., Philippon and Midrigan (2011) and Mian and Sufi (2012)). In these papers, the decline in housing values leads to a decline in aggregate demand and eventually a recession. In the finance literature, some papers focus on how firms' collateral value affects their investment decisions or how households' housing wealth affects their propensity to engage in self employment (e.g., Chaney, Sraer and Thesmar (2012), Adelino, Schoar and Severino (2013) and Fort, Haltiwanger, Jarmin and Miranda (2013)). Different from these papers that investigate how one's financial constraints affect one's own decisions, we study how agents' financial constraints affect principals' organizational form decisions and eventually their growth. In our paper, a decrease in collateralizable housing wealth makes an agent unattractive to a principal by decreasing the power of incentives. As a result, chains that would otherwise have found franchising attractive and have two ways to expand (through company-owned outlets or franchised outlets) are now more constrained, and hence open fewer stores and create fewer jobs. This is another channel through which deleveraging can affect economic growth.

The rest of the paper is organized as follows. We describe the data in Section 2. In Section 3, we develop the empirical model starting with a theoretical principal-agent framework. The estimation results are discussed in Section 4. Section 5 quantifies how much financial constraints of potential franchisees influence the franchising decision of chains. We conclude in Section 6.

2 Data

2.1 Data Sources and Variable Definitions

In this section, we describe our main data sources and how we measure the variables of interest. Further details on these can be found in Appendix A.

Our data on franchised chains, or franchisors, are from various issues of the Entrepreneur magazine's "Annual Franchise 500" surveys and the yearly "Source Book of Franchise Opportunities," now called "Bond's Franchise Guide." Our data are about business-format franchised chains. Business-format franchisors are those that provide "turn-key" operations to franchisees in exchange for the payment of royalties on revenues and a fixed upfront franchise fee. These franchisors account for all of the growth in number of franchised outlets since at least the 1970's (see Blair and

additional source of incentives beyond residual claims.

Lafontaine (2005), Figure 2-1), and have played an important role in the growth of chains in the U.S. economy. According to the Census bureau, business-format franchisors operated more than 387,000 establishments in 2007, and employed a total of 6.4 million employees. Traditional franchising, which comprises car dealerships and gasoline stations, accounted for the remaining 66,000 establishments and 1.5 million employees in franchising.

For each franchisor in our data set, we observe when the chain first started in business and when it started franchising. We refer to the difference between the two as the waiting time. For example, if a chain starts franchising in the same year that it goes into business, the waiting time variable is zero. In addition, we observe the U.S. state where each chain is headquartered, its business activity, the amount of capital required to open an outlet (Capital Required) and the number of employees that the typical outlet needs (Number of Employees). We view the Capital Required and Number of Employees needed to run the business as intrinsically determined by the nature of the business concept, which itself is intrinsically connected to the brand name. As such, we treat these characteristics as fixed over time for a given franchisor. Finally, for each year when a franchised chain is present in the data, we observe the number of company-owned outlets and the number of franchised outlets. These two variables describe a chain's growth pattern over time.

We expect differences in the type of business activity to affect the value of franchising for the chains. We therefore divide the chains among six "sectors" according to their business activity: 1- the set of chains that sell to other businesses rather than end consumers (Business Products and Services), 2- restaurants and fast-food (Restaurants), 3- home maintenance and related services, where the service provider visits the consumer at home (Home Services), 4- services consumed at the place of business of the service provider, such as health and fitness, or beauty salons (Go To Services), 5- the set of chains that sell car-related products and repair services (Auto; Repair), and 6- retail stores (Retailer).[4]

Our main explanatory variable of interest, however, is a measure of average potential franchisee collateralizable wealth in a region. We construct this variable by combining information from several sources. First, we obtained yearly housing values per state from the Federal Housing Finance Agency and the Census Bureau. Second, we obtained yearly data about home ownership rates across states from the Census Bureau. Finally, we obtained a region/year-level measure of the average proportion of mortgage outstanding for homeowners using data from the joint Census-Housing and Urban Development (HUD) biennial reports. They summarize information on mortgages on a regional basis (Northeast, Midwest, South and West). Since the reports are biennial, we ascribe the value to the year of, and to the year before, the report. As the first report was published in 1985, this implies that the data we need to generate our main explanatory variable of interest

[4]We exclude hotel chains from our data because we have too few of them in our sample, and the type of services they offer cannot easily be grouped with the categories we use. Moreover, in this industry, firms use a third contractual form, namely management contracts, in addition to franchising and company ownership.

begin in 1984. We then combine this region-level information with the state-level time series of housing value and home ownership rate to calculate the average collateralizable housing wealth per household for each state/year: $(1 -$ the average proportion of mortgage still owed$)\times$(the home ownership rate)$\times$(housing value). This is our measure of Collateralizable Housing Wealth. See Appendix A for details. This variable should be viewed as a shifter for the distribution of collateralizable housing wealth from which potential franchisees will be drawn.

2.2 Linking Chain-Level and State-Level Data

Because we are interested in how chains grow as well as how long they wait until they begin franchising after starting their business, we need to observe the macroeconomic conditions that each chain faces from the time it starts its business. We therefore combine the data on chains with our state/year collateralizable wealth and other yearly state-level macroeconomic data, namely per capita Gross State Product (GSP), which we interpret as a measure of average yearly income, and yearly state population. We could link the chain-level data with the state-level data based on where the headquarter of each chain is. But the macroeconomic conditions in a chain's headquarter state may not capture well the environment faced by the chain as it expands.

Our sample consists of 934 franchised chains headquartered in 48 states, all of which started in business – and hence also franchising – in 1984 or later. In other words, the franchised chains in our data are mostly young chains. Franchised or not, chains typically expand first in their state of headquarters and then move on to establish outlets in other, mostly nearby or related states (e.g. see Holmes (2011) for the case of Wal-Mart). We can see this tendency in our data because in post-1991 survey years, franchisors report the states where they operate the most outlets. For example, one of the largest chains in our data is Two Men and a Truck, a Michigan-based chain founded in 1984 that provides moving services. It started franchising in 1989 and had 162 franchised and 8 company-owned outlets in 2006. Two Men and a Truck had more outlets in Michigan than anywhere else until 2005, more than 20 years after its founding. Its second largest number of outlets was in Ohio until the late 1990's. In 2006, Florida became the state where it had its second largest number of outlets. It took until 2006, 22 years after founding, for its number of outlets in Florida to become larger than its number of outlets in Michigan.

Given this typical expansion pattern, to link the data on chains and the macroeconomic data, we use the information for the 1049 franchisors in our data set that we observe at least once within 15 years after they start franchising to construct a square matrix,[5] the element (i, j) of which is the percentage of franchisors that are headquartered in state i and report state j as the state where they have the most outlets. We use only one year of data per franchisor, namely the latest year within this 15 year period, to construct the matrix. The resulting matrix, in Appendix A.4, confirms that

[5]Note that we include for this exercise some chains that are excluded from our main analyses for lack of data on other variables.

most young chains operate most of their outlets in the state where they are headquartered. This can be seen by the fact that the diagonal elements of the matrix are fairly large, typically larger than any off-diagonal element. However, holding the state of origin constant and looking along a row in this matrix, it is also clear that franchisors headquartered in certain, typically smaller states, view some other, usually nearby states, as good candidates to expand into even early on in their development. For example, 25% of the franchisors from Nevada have more outlets in California than in any other state. Only 13% of them report having more outlets in Nevada than anywhere else. Similarly, many franchisors headquartered in Utah (48% of them) have expanded into California to a greater extent than they have in their own state. Only 36% of them have most of their establishments in Utah proper.

We interpret this matrix as an indication of where the franchisors from each state are most likely to want to expand during the period that we observe them. We therefore use the elements of this matrix, along a row – i.e., given a state of headquarters – to weigh our state/year-level macroeconomic variables and match them to our chain/year-level variables. In our robustness analysis, we consider an alternative matrix where we account for the proportion of each chain's outlets in the top three states in the construction of the weights rather than only using information on which state is the top state. Appendix A provides further details on the construction of that matrix as well.

2.3 Summary Statistics and Basic Data Patterns

Summary statistics for all our variables, including chain characteristics such as the waiting time and the number of outlets, as well as our weighted macroeconomic and collateralizable wealth measures, are shown in Table 1. We also present summary statistics for our one national-level macroeconomic variable, the national interest rate, which we measure using the effective federal funds rate, obtained from the Federal Reserve.

Table 1 shows that the chains in our data waited on average 3 years after starting in business to become involved in franchising. The majority of the chains are small, and they rely heavily on franchising: the mean number of franchised outlets is 35.56, while the mean number of company-owned outlets is only 3.43. Though not reported in this Table, our data also indicate that the average yearly growth in company-owned outlets before a chain starts franchising is 0.59. After they start franchising, the chains tend to open mostly franchised outlets. For example, the average change in the number of franchised outlets five years after a chain starts franchising is 38.52, while the average change in number of company-owned outlets during these five years is 0.45. Similarly, the average number of additional franchised and company-owned outlets in the ten years after a chain starts franchising are 44.21 and 3.67, respectively.

In terms of our chain-level explanatory variables, Table 1 shows that the typical establishment

Table 1: Summary Statistics

	Mean	Median	S. D.	Min	Max	Obs
Waiting Time (Years)	3.17	2	3.16	0	18	934[a]
Company-owned Outlets	3.43	1	7.40	0	106	3820[b]
Franchised Outlets	35.56	17	44.28	0	285	3820
Required Employees	5.61	3.50	7.79	0.50	112.5	934
Required Capital (Constant 82-84 $100K)	0.93	0.55	1.45	0	19.72	934
Business Products & Services	0.16	0	0.36	0	1	934
Restaurants	0.21	0	0.41	0	1	934
Home Services	0.12	0	0.33	0	1	934
Go To Services	0.21	0	0.41	0	1	934
Auto; Repair	0.06	0	0.23	0	1	934
Retail	0.24	0	0.43	0	1	934
Coll. Housing Wealth (82-84 $10K)	3.62	3.34	1.31	1.83	14.17	1104[c]
Population (Million)	8.84	8.23	5.52	0.52	31.68	1104
Per-Capita Gross State Product (82-84 $10K)	1.89	1.79	0.63	1.22	7.47	1104
Interest Rate (%)	5.33	5.35	2.41	1.13	10.23	23[d]

[a]At the chain level
[b]At the chain/year level
[c]At the state/year level, for 48 states between 1984 and 2006.
[d]At the year level

in these chains employs five to six employees. Chains also are not very capital intensive, with an average amount of capital required to open an outlet of $93,000. The variation around this mean, however, is quite large. Franchisors in our data are also distributed fairly evenly across our main sectors, with the exception of Auto; Repair which is the least populated of our sectors.

Finally, the descriptive statistics for our state/year-level weighted macroeconomic variables show that the average collateralizable housing wealth was about $36K in 1982-84 constant dollars over the 1984 - 2006 period, while per capita real income averaged $19K over the same period. (See Table A.1 and related discussion in Appendix A.4 for more on the descriptive statistics for these variables using different weights.)

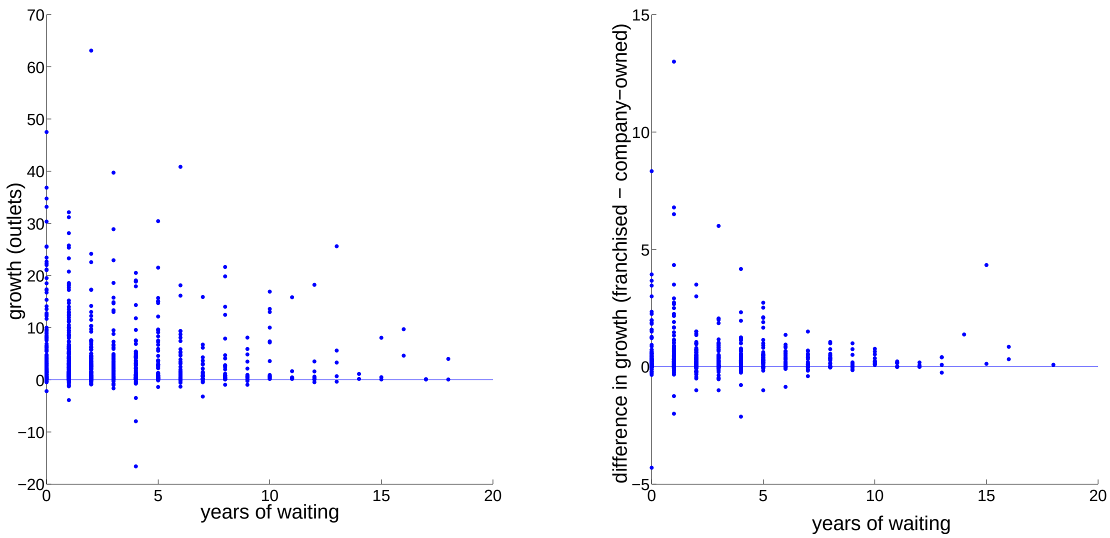
Figure 1(a) gives more detail about the overall growth in the number of outlets across the chain/years in our data. Specifically, for each chain, we compute the yearly change in the total number of outlets (including both company-owned outlets and franchised outlets), and then take the average over the years we observe each chain.[6] We show this average yearly growth in number of outlets against the chain's waiting time (i.e., the number of years between when it starts in business and when it begins franchising). Figure 1(a) shows that chains that enter into franchising faster also grow faster on average.

[6]When the data on the number of outlets is missing for all chains, as in, for example, 1999 when our data source was not published, we compute the change in number of outlets from 1998 to 2000 and divide the result by 2 to compute the yearly change.

Figure 1: Timing of Entry into Franchising, Overall Growth, and Difference in Franchised and Company-Owned Outlet Growth

(a) Overall Growth

(b) Difference in Franchised and Company-Owned Outlet Growth



Note: In Figure 1(a), each dot represents a chain. For each chain, we compute the yearly change in the total number of outlets, and then we average these changes across years within this chain. In Figure 1(b), each dot also represents a chain. For each chain, we calculate the change in the number of franchised and the number of company-owned outlets each year, compute the difference between these, and then normalize this difference by the total number of outlets in the chain at the beginning of the year. We then average this normalized difference across years within chains.

Similarly, we show the difference between the growth in the number of franchised outlets and the growth in the number of company-owned outlets in Figure 1(b). In this figure, for each chain, we compute the yearly change in the number of franchised outlets and the yearly change in the number of company-owned outlets separately, and then the difference between the two. We then normalize the difference by the total number of outlets at the beginning of the year in order to better capture what is relative rather than total growth. Finally, we compute the average of this normalized difference across years within chains. Figure 1(b) shows that chains that start franchising faster not only grow faster overall (per Figure 1(a)) but also grow relatively faster through franchised outlets. This is quite intuitive. Chains make decisions about entry into franchising based on their expectations of growth after entry. A chain for which franchising is particularly valuable should therefore start franchising earlier. In other words, the decisions on the timing of entry into franchising and expansion paths – in terms of both company-owned and franchised outlets – are intrinsically linked. Combining the information on entry decisions and growth, as we do in our empirical model below explicitly, therefore will generate better estimates of the effect of agent collateral housing wealth.

3 The Model

In this section, we develop our empirical model of franchisors' franchising decision. We begin with a theoretical principal-agent model with a typical chain facing a set of heterogeneous potential franchisees. Franchisees differ in the amount of collateral they can put forth. The model shows how differences in collateralizable wealth affect a franchisee's effort level and, thus, the chain's decisions to expand at the margin via a franchised or a company-owned outlet. This simple theoretical model provides intuition and guides our empirical specification. In Section 4, we take the empirical model to the data and estimate the determinants of a chain's entry (into franchising) and its expansion decisions.

3.1 A Principal-Agent Model of Franchising

Suppose that revenue for a specific chain outlet can be written as a function $G(\theta, a)$. The variable θ, drawn from some distribution $F(\theta)$, captures the local conditions for that specific outlet, as well as a profit shock. Let a be the effort level of the manager/franchisee of the outlet. The revenue function is increasing in both θ and a. The cost of effort is given by a cost function $\Psi(a)$, which is increasing and strictly convex with $\lim_{a\to\infty} \Psi'(a) = \infty$ and $\Psi(a) > 0$ for all $a > 0$. Opening an outlet in this chain requires capital of I. We assume that a franchisee's liquid wealth is smaller than I so that she needs to borrow from a bank in the form of a debt contract which specifies the required repayment R as a function of the collateral C and the investment I. The repayment $R(C, I)$ is decreasing in C but increasing in I.[7]

We first describe the franchisee's effort choice and provide intuition on how her collateral amount affects this choice. We then discuss the chain's decision-making process given that it is facing a set of potential franchisees with heterogeneous collateralizable wealth.

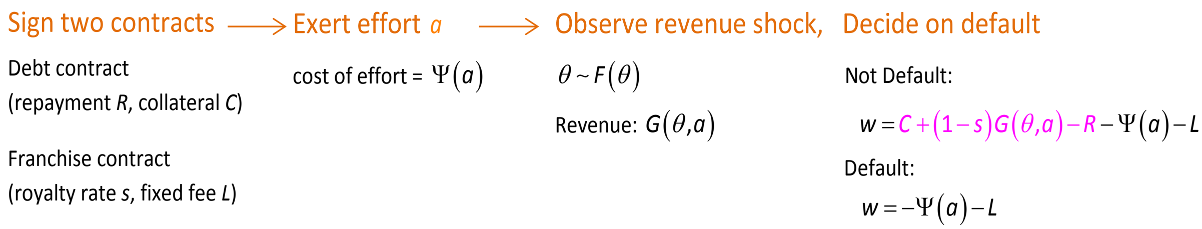
A typical franchisee's problem is illustrated in Figure 2. After signing both the franchise contract with the franchisor and the debt contract with the bank, the franchisee chooses her effort level a. The revenue shock for her outlet θ is then realized. If the franchisee chooses not to default on her obligation by paying the repayment R, she can keep her collateral C and earn her share of the revenue $(1-s)G(\theta, a)$, where s is the royalty rate, namely the share of revenues that the franchisee pays to the franchisor.[8] The franchisee's payoff is thus $C + (1-s)G(\theta, a) - R(C, I) - \Psi(a) - L$ when she does not default, where L is a lump-sum one-time fixed fee that is paid up front, at the beginning of the franchise relationship (i.e., a franchise fee).

If the franchisee chooses to default, the bank seizes the collateral C and liquidates the store. The franchisee's payoff then is $-\Psi(a) - L$. The franchisee defaults if and only if $C + (1-s)\, G(\theta, a) -$

[7] This is a simplified version of a debt contract that allows us to incorporate the main factors that we care about.

[8] Royalty payments are almost always a proportion of revenues in business-format franchising. These are typically collected monthly. So, for simplicity, we assume the franchisor is paid before the bank. This assumption does not drive our results.

Figure 2: Franchisee's Problem



$R(C,I) < 0$.[9] We define θ^* as the critical state of the world below which default occurs, implicitly determined by:

$$C + (1-s)\,G(\theta^*, a) - R(C, I) = 0. \tag{1}$$

Since, for given I in the debt contract, the repayment is decreasing in C, and revenue is increasing in the revenue shock θ, we have $\frac{\partial \theta^*}{\partial C} < 0$. In other words, as the collateral increases, the repayment is smaller and it is less likely that the franchisee will default.

Suppose the franchisee is risk averse and her utility function is $-e^{-\rho w}$, where $\rho > 0$ is her parameter of constant absolute risk aversion and w is her payoff. The franchisee chooses her effort level a to maximize her expected utility:

$$U = \int_{-\infty}^{\theta^*} - e^{-\rho[-\Psi(a)-L]} dF(\theta) + \int_{\theta^*}^{\infty} - e^{-\rho[C+(1-s)G(\theta,a)-R(C,I)-\Psi(a)-L]} dF(\theta). \tag{2}$$

In Online Appendix A, we show that when the risk aversion coefficient ρ is small, $\frac{\partial^2 U}{\partial a \partial C} > 0$ at a^*, the interior solution of this utility maximization problem. Therefore, $\frac{\partial a^*}{\partial C} > 0$, i.e., the equilibrium effort is increasing in the collateral. Intuitively, there are two effects. First, with higher collateral, the repayment is smaller and it is less likely that the franchisee will default, which leads to greater returns to marginal effort. Therefore, the more collateralizable wealth a franchisee has, the higher her effort level.[10] Second, the franchisee's payoff when she does not default is increasing in C, and

[9] We assume that the liquidation value is zero. All we really need is that it is smaller than $(1-s)G(\theta, a)$. To see this, let $W < (1-s)G$ be the liquidation value. The franchisee's payoff when defaulting is $(C + W - R)\mathbb{1}(C + W > R) - \Psi(a) - L$. We can show that when $W < (1-s)G$, her default decision depends on the sign of $C + (1-s)G - R$. More generally, all we need for our results qualitatively is that the opportunity cost of defaulting depends on the collateral and is increasing in both θ and the effort a. Thus, we could allow for other costs of defaulting such as the adverse effect of defaulting on the franchisee's credit record. Alternatively, $(1-s)G - W$ can be interpreted as the difference between the expected present value of an outlet if the franchisee does not default and that when she does default.

[10] Our model emphasizes the moral hazard problem in that we focus on how the amount of collateral that the franchisee provides affects her incentives to put forth effort. Asymmetric information – or hidden information – issues could also play a role in the franchisor's decision to require franchisees to rely on their collateral. For example, some franchisees may have a lower cost of exerting effort, and franchisors would want to select such franchisees. Since only franchisees who have a low cost of exerting effort would agree to put a lot down as collateral, the collateral requirement can help resolve this asymmetric information problem as well. Note that in such a scenario, the selected franchisees also work hard, which is consistent with the intuition we highlight in our model. It is unclear, therefore, what kind of intrinsic quality of a manager would matter without interacting with the effort they provide. Moreover,

so the marginal utility from the additional payoff generated through working harder is decreasing in C. Thus, increasing C also affects effort negatively due to the diminishing utility from wealth. For small ρ, the first positive effect of C on incentives dominates the second negative effect. (See Online Appendix A for more details.) Let $\tilde{U}(s, L, C)$ be the franchisee's expected utility at her optimal effort level.

We now describe the franchisor's problem.[11] Suppose that for each specific opportunity that a franchisor has for opening an outlet, there are N potential franchisees each of whom has a collateralizable wealth C_i drawn from a distribution F_C. Given the franchise contract (s, L) that specifies the royalty rate s and the fixed fee L,[12] some potential franchisees may find that their participation constraint ($\tilde{U}(s, L, C_i) > -e^{-\rho w}|_{w=C_i} = -e^{-\rho C_i}$) is not satisfied. From the remaining set of potential franchisees, the chain picks the one that generates the most expected profit. The expected profit from a franchisee with collateral C_i is $\tilde{\pi}_f(s, L, C_i) = \int_{-\infty}^{\infty} sG(\theta, a^*(s, L, C_i))\, dF(\theta) + L$, where $a^*(s, L, C_i)$ is the franchisee's optimal effort level. The expected profit from establishing a franchised outlet is therefore $\max_{i=1,\ldots,N} \tilde{\pi}_f(s, L, C_i)\, \mathbb{1}\left(\tilde{U}(s, L, C_i) > -e^{-\rho C_i}\right)$. The franchisor compares this expected profit to the expected profit from a company-owned outlet, denoted by $\tilde{\pi}_c$.[13] The franchisor can also choose to give up this opportunity. Thus, the franchisor's expected profit is

$$\tilde{\pi}(s, L) = E_{(C_1,\ldots,C_N)} \max\left\{ \max_{i=1,\ldots,N} \tilde{\pi}_f(s, L, C_i)\, \mathbb{1}\left(\tilde{U}(s, L, C_i) > -e^{-\rho C_i}\right),\, \tilde{\pi}_c,\, 0 \right\}. \tag{3}$$

Intuitively, given that a franchisee i's effort is increasing in her collateral C_i, the expected profit from opening a franchised outlet shifts upwards when there is a first-order stochastic dominating shift in the distribution of C_i. As a result, the franchisor is more likely to open a franchised outlet. In other words, franchisees' financial constraints affect the franchisors' organizational form decisions.

Since we cannot derive a full analytical solution to a general model such as the one above, with uncertainty of defaulting and heterogeneous franchisees, in the next section, we use a parameterized

franchisors use several mechanisms to evaluate and screen potential franchisees over a period of several months typically, including face-to-face meetings, often extensive periods of training, and so on. Finally, we focus on effort and moral hazard because franchisors indicate that franchisee effort is a major reason why they use franchising. Some franchisors include an explicit clause in their franchise contracts imposing a requirement for best and full-time effort. For example, McDonald's 2003 contract includes the following clause: 13. *Best efforts.* Franchisee shall diligently and fully exploit the rights granted in this Franchise by personally devoting full time and best efforts [...] Franchisee shall keep free from conflicting enterprises or any other activities which would be detrimental or interfere with the business of the Restaurant. [McDonald's corporation Franchise Agreement, p. 6.]

[11] As will be clear below, we do not allow for strategic considerations in the growth and entry decisions of the chains in our data. The young small franchised chains that we focus on typically choose to go into business only if they can design a product and concept that is different enough from existing ones to give them some specific intellectual property. As a result of this differentiation, we do not expect that strategic considerations play much of a role in the early growth and entry into franchising decisions that we are interested in.

[12] In practice, a franchisor typically sets up a single franchise contract for all franchisees.

[13] We assume that a minimum level of effort can be induced even for an employed manager. This can be thought of as an observable component of effort or a minimum standard that can be monitored at low cost.

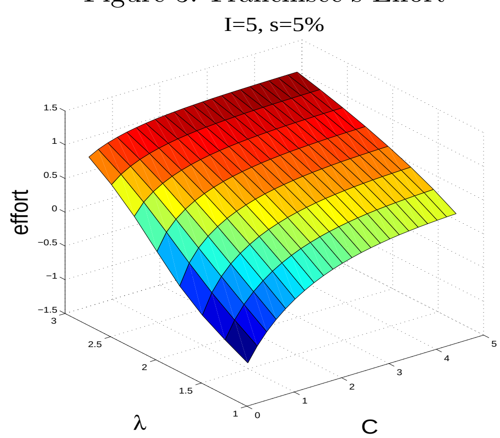
version of the model to illustrate some properties of the franchisee's behavior and the franchisor's profit function.

3.2 An Illustrative Example

We describe the parameterized version of the model fully in Appendix B, and only give an overview here. We assume that the revenue function $G(\theta, a) = \theta + \lambda a$, where λ captures the importance of the outlet manager's effort. We normalize the effort of a hired manager to $a_0 = 0$.

To see how a franchisee's effort varies with the importance of the manager's effort (λ) and the collateralizable wealth of a potential franchisee (C), we compute the optimal effort level of a franchisee. Results are shown in Figure 3. The figure illustrates our model prediction above that the franchisee's choice of effort level is increasing in C. When the collateral C increases, the franchisee has greater incentives to work hard as the return to marginal effort is higher. Per the standard result in the literature, Figure 3 also shows that the optimal effort level is increasing in the importance of the manager's effort λ. A similar intuition applies: as λ increases, the marginal utility of effort increases, which leads to a higher optimal effort level.

Figure 3: Franchisee's Effort

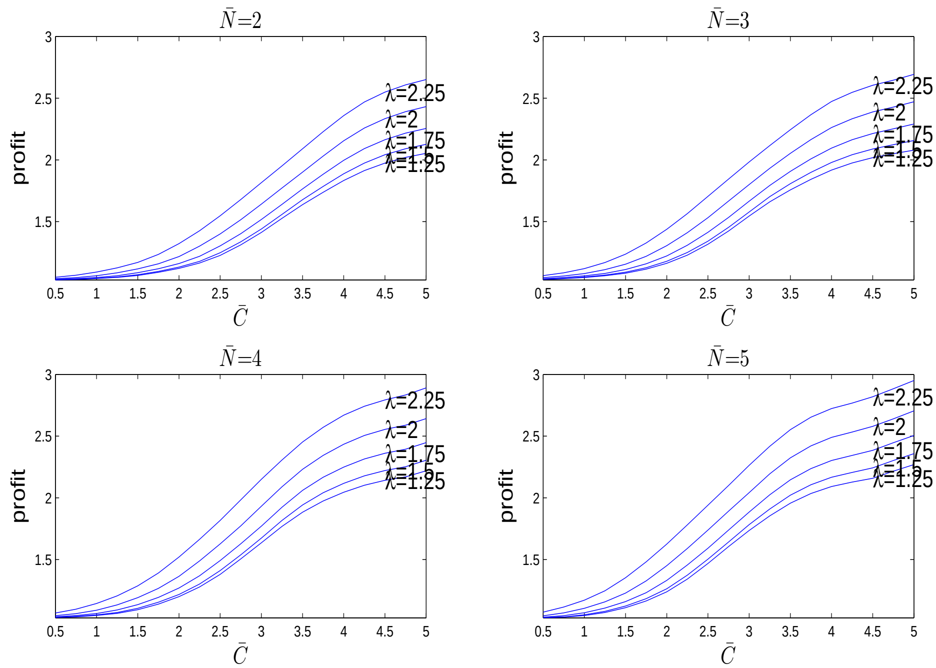


The parameterized model also yields a number of intuitive properties for the franchisor's expected profit function. Figure 4 provides a graphical illustration of these properties. For the comparative statics shown in this Figure, we assume that the distribution of collateralizable wealth can be parameterized by its mean $\bar{C}$. In addition, different from the model described in Section 3.1, we now allow the number of potential franchisees to be drawn from a distribution $F_N(\cdot;\bar{N})$, where $\bar{N}$ is the mean. We also allow the franchisor to choose the franchise contract (s, L) optimally given the distributions $F_C(\cdot;\bar{C})$ and $F_N(\cdot;\bar{N})$. In other words, in Figure 4, we show

$$\tilde{\pi} = \max_{(s,L)} E_{N|F_N(\cdot;\bar{N})} E_{(C_1,\dots,C_N)|F_C(\cdot;\bar{C})} \max\left\{ \max_{i=1,\dots,N} \tilde{\pi}_f\left(s, L, C_i\right) \mathbb{1}\left(\tilde{U}\left(s, L, C_i\right) > -e^{-\rho C_i}\right), \tilde{\pi}_c, 0 \right\}. \tag{4}$$

Note that the profit from opening a company-owned outlet in our example is 1 given the normalization that a hired manager's effort a_0 is 0.

Figure 4: Franchisor's Expected Profit: $\tilde{\pi}$ in Equation (4)



Four features of the expected profit for the franchisor can be seen from Figure 4. First, the franchisor's expected profit is increasing in the average collateralizable wealth of the potential franchisees, $\bar{C}$. This is consistent with the intuition explained above. Since the franchisor's expected profit is increasing in a franchisee i's effort, which is itself increasing in C_i, an increase in $\bar{C}$ increases the chain's expected profit from franchising. In that sense, our model explains the common practice of franchisors to insist that franchisees put their own wealth at stake. Second, the franchisor's expected profit is increasing in the importance of the franchisee effort λ as a larger λ also means a higher incentive for the franchisee to exert effort. Third, the slope of the franchisor's profit with respect to C is increasing in λ, implying that the marginal effect of C on profit is increasing in λ. This is again intuitive because the revenue function is $\theta + \lambda a$, where the effort level is increasing in C. Fourth and finally, as we can see by looking across the four panels in Figure 4, the franchisor's profit is increasing in the average number of potential franchisees $\bar{N}$. The intuition is closely related to that in the first point. For a given distribution of collateralizable wealth, more potential franchisees mean that there is a greater chance of finding a franchisee with sufficient collateralizable wealth to make her a good candidate for the chain.

3.3 The Empirical Model

Our data describe the timing of when a chain starts franchising and how it grows – and sometimes shrinks – over time through a combination of company-owned and franchised outlets. The model above gives predictions on the relative attractiveness of opening a franchised outlet to a chain, which then determines the timing of its entry into franchising and its growth decisions. One empirical approach we could adopt given this would be to parameterize the model above as in Appendix B and take its implications to data and estimate the primitives of that model. However, this approach requires that we make functional form assumptions on primitives that the data and context provide little information about. We therefore take a different approach and use the findings above as guidance to specify reduced-form profit functions directly.

Model Primitives

We assume that opportunities to open outlets in the chains arrive exogenously. For example, an opportunity can arise when a site in a mall becomes available. We assume that the arrival of opportunities follows a Poisson process with rate m_i for chain i, where $m_i = exp(m + u_{mi})$ and u_{mi}'s are i.i.d. and follow a truncated normal distribution with mean 0 and variance σ_m^2, truncated such that the upper bound of m_i is 200 per year.

When an opportunity τ arrives in year t after chain i has started franchising, the franchisor can choose to open a company-owned outlet, a franchised outlet or pass on the opportunity. We assume that the value of a company-owned outlet and that of a franchised outlet for the chain given an opportunity τ can be written as, respectively,

$$\begin{aligned} \pi_{ci\tau} &= \boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci} + \varepsilon_{ci\tau}, \\ \pi_{fi\tau} &= \pi_{ci\tau} + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi} + \varepsilon_{fi\tau}, \end{aligned} \tag{5}$$

where $\boldsymbol{x}_{it}^{(c)}$ is a vector of observable chain i-, or chain i/year t-specific variables that affect the profitability of opening a company-owned outlet. The vector $\boldsymbol{x}_{it}^{(f)}$ consists of the observables that influence the profitability of a franchised outlet relative to a company-owned outlet. According to the results in Section 3.2, this vector includes the average collateralizable housing wealth of chain i's potential franchisee pool. It also includes determinants of the importance of manager effort such as the number of employees, given that employee supervision is a major task for managers in the types of businesses that are franchised, as well as the interaction of the number of employees and the average collateralizable wealth, per the third finding on chain profit described above. Details on these two vectors of covariates, $\boldsymbol{x}_{it}^{(c)}$ and $\boldsymbol{x}_{it}^{(f)}$, are given in Section 4 where we explain the estimation results.

In equation (5), u_{ci} and u_{fi} represent the unobserved profitability of a company-owned and a franchised outlet respectively for chain i. The former captures in particular the unobserved value of the chain's product. The latter accounts for the fact that the business formats of some chains are more amenable to codification, and thus franchising, than others. The unobserved profitability of franchising will be greater for such chains. The error terms $\varepsilon_{ci\tau}$ and $\varepsilon_{fi\tau}$ capture the unobserved factors that affect the profitability of each type of outlet given opportunity τ. We assume that $\varepsilon_{ci\tau} = \epsilon_{ci\tau} - \epsilon_{0i\tau}$ and $\varepsilon_{fi\tau} = \epsilon_{fi\tau} - \epsilon_{0i\tau}$, and that $(\epsilon_{ci\tau}, \epsilon_{fi\tau}, \epsilon_{0i\tau})$ are i.i.d. and drawn from a type-1 extreme value distribution.

Chains' Growth Decisions

Given the above primitives of the model, and using $\boldsymbol{x}_{it} = \left(\boldsymbol{x}_{it}^{(c)}, \boldsymbol{x}_{it}^{(f)}\right)$, the probability that chain i opens a company-owned outlet conditional on the arrival of an opportunity is

$$p_{ac}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right) = \frac{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci}\right)}{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci}\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci} + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1} \tag{6}$$

after chain i has started franchising. In this equation, the subscript a stands for "after" (after starting franchising) and the subscript c stands for "company-owned." Similarly, the probability of opening a franchised outlet conditional on the arrival of an opportunity is

$$p_{af}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right) = \frac{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci} + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right)}{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci}\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci} + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1}. \tag{7}$$

If, however, chain i has not started franchising by year t, the probability of opening a company-owned outlet conditional on the arrival of an opportunity is

$$p_{bc}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right) = \frac{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci}\right)}{\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + u_{ci}\right) + 1}, \tag{8}$$

where the subscript b stands for "before" (before starting franchising).

Given that the opportunity arrival process follows a Poisson distribution with rate m_i for chain i, the number of new company-owned outlets opened in year t before chain i starts franchising follows a Poisson distribution with mean $m_i p_{bc}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right)$. Similarly, the number of new company-owned or new franchised outlets opened after chain i starts franchising also follows a Poisson distribution with mean $m_i p_{ac}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right)$ or $m_i p_{af}\left(\boldsymbol{x}_{it}, u_{ci}, u_{fi}\right)$.

It is difficult to separately identify the opportunity arrival rate and the overall profitability of opening an outlet. For example, when we observe that a chain opens a small number of outlets per year, it is difficult to ascertain whether this is because the chain had only a few opportunities during the year, or because it decided to take only a small proportion of a large number of opportunities. That said, we do have some information that allows us to identify the overall profitability of an outlet.[14] However, this information is not very powerful. Hence, we allow separate constants in the opportunity arrival rate and the overall profitability of an outlet, but set u_{ci} to be 0. We assume that u_{fi} follows a normal distribution with mean 0 and variance σ_u^2.

Chains' Decision to Enter into Franchising

The start of franchising is costly because franchisors must develop operating manuals, contracts, disclosure documents and processes to support and control franchisees. The franchisor must devote significant amounts of time to these activities, in addition to relying on lawyers and accountants.[15] Note that all of these costs are sunk: none of them are recoverable in the event that the chain decides to stop franchising or goes out of business. Let ω_{it} be the sunk cost that chain i has to pay to start franchising. We assume that ω_{it} follows a log-normal distribution with mean and variance parameters ω and σ_ω^2. It turns out that the variance is very large. To fit the data better, we also allow some probability mass at the entry cost being infinity. This can be interpreted as the chain's owner not being aware that franchising exists, or that it could be a viable option for her kind of business. We capture this in our model by allowing future franchisors to be aware or thinking about franchising in their first year in business with some probability $q_0 \leq 1$. For every other year after the first, franchisors who are not yet aware that franchising is a viable option for their business become aware with some probability, $q_1 \leq 1$. Once the potential franchisor becomes aware, at the beginning of each year from that point on, she decides whether to pay the sunk cost ω_{it} to start franchising. The entry-into-franchising decision therefore depends on how the value of entry into franchising minus the setup cost compares with the value of waiting.

The value of entry into franchising is the expected net present value of all future opportunities after entry into franchising. The expected value of an opportunity τ after entry into franchising is

$$
\begin{aligned}
&E_{(\varepsilon_{ci\tau},\varepsilon_{fi\tau})} \max\{\pi_{ci\tau}, \pi_{fi\tau}, 0\} \\
&= \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1\right).
\end{aligned} \tag{9}
$$

Given that the expected number of opportunities is m_i, the expected value of all opportunities in period t after the chain starts franchising is $m_i \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1\right)$.

[14] We know about the accumulated number of company-owned outlets they have chosen to open (minus any closings) before they started franchising, which provides information on their overall growth before they have the option to franchise. Once the relative profitability of a franchised outlet is identified, the ratio of the overall growth before and after a chain starts franchising identifies the baseline profitability, i.e., the profitability of a company-owned outlet. If a chain is very profitable even when it is constrained to open only company-owned outlets, adding the option of franchising has a smaller impact on its overall growth, and vice versa.

[15] There are specialized consulting firms that can help with this process. Hiring such firms easily costs a few hundreds of thousands of dollars, however. These are substantial amounts for most of the retail and small-scale service firms in our data, and the owner still has to spend time investigating and considering how best to organize a franchise.

We assume that $\boldsymbol{x}_{it}$ follows a Markov process. Thus, the value of entry satisfies

$$VE\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) = m_i \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1\right) \\ + \delta E_{\boldsymbol{x}_{it+1}|\boldsymbol{x}_{it}} VE\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right), \tag{10}$$

where δ is the discount factor and $\boldsymbol{u}_i = (u_{mi}, u_{fi})$ are the unobservable components in the opportunity arrival rate and in the relative profitability of a franchised outlet, respectively.

If chain i has not entered into franchising at the beginning of year t, it can only choose to open a company-owned outlet – or do nothing – when an opportunity arises in year t. The expected value of opportunities in year t is therefore $m_i E_{\varepsilon_{ci\tau}} \max\{\pi_{ict}, 0\} = m_i \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + 1\right)$. As for the continuation value, note that if the chain pays the sunk cost to enter into franchising next year, it gets the value of entry $VE\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right)$. Otherwise, it gets the value of waiting $VW\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right)$. So the value of waiting this year is

$$VW\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) = m_i \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + 1\right) \\ + \delta E_{\boldsymbol{x}_{it+1}|\boldsymbol{x}_{it}} E_{\omega_{it+1}} \max\left\{VE\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right) - \omega_{it+1},\ VW\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right)\right\}. \tag{11}$$

Let $V\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right)$ be the difference between the value of entry and the value of waiting: $V\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) = VE\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) - VW\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right)$. Subtracting equation (11) from equation (10) yields

$$V\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) = m_i \left[\log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + \exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c + \boldsymbol{x}_{it}^{(f)}\boldsymbol{\beta}_f + u_{fi}\right) + 1\right) - \log\left(\exp\left(\boldsymbol{x}_{it}^{(c)}\boldsymbol{\beta}_c\right) + 1\right)\right] \\ + \delta E_{\boldsymbol{x}_{it+1}|\boldsymbol{x}_{it}} E_{\omega_{it+1}} \min\left\{\omega_{it+1},\ V\left(\boldsymbol{x}_{it+1},\boldsymbol{u}_i\right)\right\} \tag{12}$$

Chain i starts franchising at the beginning of year t if and only if the difference between the value of entry and the value of waiting is larger than the entry cost, i.e., $V\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right) \geq \omega_{it}$. Since we assume that the entry cost shock ω_{it} follows a log-normal distribution with mean and standard deviation parameters ω and σ_ω, the probability of entry conditional on i thinking about franchising is

$$g\left(\boldsymbol{x}_{it};\boldsymbol{u}_i\right) = \Phi\left(\frac{\log V\left(\boldsymbol{x}_{it};\boldsymbol{u}_i\right) - \omega}{\sigma_\omega}\right), \tag{13}$$

where $\Phi(\cdot)$ is the distribution function of a standard normal random variable.

Likelihood Function

The parameters of the model are estimated by maximizing the likelihood function of the sample using simulated maximum likelihood. For each chain i in the data, we observe when it starts in business (treated as exogenous) and when it starts franchising (denoted by F_i). So, one component of the likelihood function is the likelihood of observing F_i conditional on chain i's unobservable component of the arrival rate and its unobservable profitability of opening a franchised outlet:

$$p_i \left(F_i | \boldsymbol{u}_i \right). \tag{14}$$

See Online Appendix B for details on computing this component of the likelihood.

We also observe the number of company-owned outlets (denoted by n_{cit}) and the number of franchised outlets (denoted by n_{fit}) for $t = F_i, ..., 2006$.[16] Therefore, another component of the likelihood function is the likelihood of observing $(n_{cit}, n_{fit}; t = F_i, ..., 2006)$ conditional on chain i's timing of entry into franchising (F_i) and the unobservables $(\boldsymbol{u}_i)$:

$$p_i \left(n_{cit}, n_{fit}; t = F_i, ..., 2006 | F_i; \boldsymbol{u}_i \right). \tag{15}$$

For more than 29% of the chains in the data, the number of outlets decreases at least once during the time period we observe this chain. To explain these negative changes in number of outlets, we assume that an outlet, franchised or company-owned, can exit during a year with probability γ. The number of company-owned outlets in year t is therefore

$$n_{cit} = n_{cit-1} - \text{exits}_{cit-1} + (\text{new outlets})_{cit}, \tag{16}$$

where exits_{cit-1} follows a binomial distribution parameterized by n_{cit-1} and γ. As explained above, $(\text{new outlets})_{cit}$ follows a Poisson distribution with mean $m_i p_{ac} \left(\boldsymbol{x}_{it}, \boldsymbol{u}_i \right)$ or $m_i p_{bc} \left(\boldsymbol{x}_{it}, \boldsymbol{u}_i \right)$ depending on whether the chain starts franchising before year t or not. Similarly,

$$n_{fit} = n_{fit-1} - \text{exits}_{fit-1} + (\text{new outlets})_{fit}, \tag{17}$$

where $(\text{new outlets})_{fit}$ follows a Poisson distribution with mean $m_i p_{af} \left(\boldsymbol{x}_{it}, \boldsymbol{u}_i \right)$ and exits_{fit-1} follows a binomial distribution parameterized by n_{fit-1} and γ. The recursive equations (16) and (17) are used to derive the probability in (15). See Online Appendix B for further details.

Since our data source is about franchised chains, we only observe a chain if it starts franchising before the last year of our data, which is 2006. Therefore, the likelihood of observing chain i's choice as to when it starts franchising (F_i) and observing its outlets $(n_{cit}, n_{fit}; t = F_i, ..., 2006)$ in the sample depends on the density of $(F_i, n_{cit}, n_{fit}; t = F_i, ..., 2006)$ *conditional* on the fact that we observe it, i.e., $F_i \leq 2006$. This selection issue implies, for example, that among the chains that start in business in the later years of our data, only those that find franchising particularly appealing will appear in our sample. Similar to how this is handled in a regression where selection

[16]Since our data source is a survey on franchisors, we only observe the number of outlets of a chain after it starts franchising. But we actually do not observe it for all years between F_i and 2006, the last year of our sample, for two reasons. First, as explained in Appendix A, we are missing data for all franchisors for 1999 and 2002. Second, some chains may have exited before 2006. For simplicity in notation, we omit this detail in describing the likelihood function in this section. Online Appendix B provides details on how to deal with this missing data issue.

is based on a response variable (such as a Truncated Tobit model), we account for this in the likelihood function by conditioning as follows:

$$\begin{aligned}\mathcal{L}_i &= \Pr\left(F_i, n_{cit}, n_{fit}; t = F_i, ..., 2006 | F_i \leq 2006\right) \\ &= \frac{\int p_i\left(F_i | \boldsymbol{u}_i\right) \cdot p_i\left(n_{cit}, n_{fit}; t = F_i, ..., 2006 | F_i; \boldsymbol{u}_i\right) dP_{\boldsymbol{u}_i}}{\int p_i\left(F_i \leq 2006 | \boldsymbol{u}_i\right) dP_{\boldsymbol{u}_i}}.\end{aligned} \tag{18}$$

Our estimates of the parameters $\left(\boldsymbol{\beta}_c, \boldsymbol{\beta}_f, \gamma, m, \sigma_m, \sigma_u, \omega, \sigma_\omega, q_0, q_1\right)$ maximize the log-likelihood function obtained by taking the logarithm of (18) and summing up over all chains.

Identification

We now explain the sources of identification for our estimated parameters. As mentioned above, collateralizable housing wealth is expected to affect the relative profitability of opening a franchised outlet via its effect on the franchisee's incentives to put forth effort. It may also, however, affect the general profitability of an outlet in the chain by affecting the demand for the chain's products or services. We can separately identify these effects because we observe two growth paths, the growth path in the number of company-owned and the growth path in the number of franchised outlets. Variation in the relative growth of the number of franchised outlets helps us identify the effect of collateralizable housing wealth via the incentive (or supply) channel, while variation in the overall growth of the chain allows us to identify the effect of collateralizable housing wealth via the demand channel.

Variation in the total number of outlets arises not only from variation in the profitability of outlets for this chain, however, but also from variation in the arrival rate that is specific to this chain. As we cannot separately identify these effects, we put covariates in the general profitability of an outlet only.

The observed shrinkage in the number of outlets gives us a lower bound estimate of the outlet exit rate. An "exclusion" restriction further helps us identify this parameter: for some chains in our data, we observe them in the year that they start franchising. The franchised outlets that a chain has in the year when it starts franchising presumably are new franchised outlets opened that year rather than a combination of newly opened and closed outlets. Hence the number of franchised outlets in that year should not incorporate any exits.

Dispersion in the total number of outlets identifies the standard deviation of the arrival rate (σ_m). Dispersion in relative growth identifies the standard deviation of the unobserved relative profitability of a franchised outlet (σ_u). Given the growth patterns, data on waiting time (the difference between when a chain starts its business and when it starts franchising) identifies the distribution of the cost of entering into franchising, i.e., (ω, σ_ω). Furthermore, the probability of not being aware of franchising in the first year in business, $1 - q_0$, also is identified by the observed variation in waiting time as it is essentially the probability mass of the entry cost at infinity. The identification for q_1, the probability of thinking about franchising in later years, is similar.

4 Estimation Results

4.1 Baseline Estimation Results

The estimation results, in Table 2, indicate that both population and per-capita gross state product, our measure of income, affect the profitability of outlets positively, presumably by increasing the demand for the products of the chains. Collateralizable housing wealth, however, has a negative effect on the general profitability of a chain's outlets. In other words, once we control for income (per-capita gross state product) and our other macroeconomic variables, collateralizable housing wealth reduces how much consumers want to consume the products of the chains. One potential explanation for this result is that rent may be high in those regions where collateralizable housing wealth is high, making outlets less profitable. Alternatively, for given income, higher wealth may indeed have a negative effect on the demand for the type of products sold by franchised chains (e.g., fast food).

Collateralizable housing wealth, however, has a positive effect on the value of opening a franchised outlet relative to opening a company-owned outlet in our data. In other words, when franchisees have more collateral to put forth, the chains increase their reliance on franchising relative to company ownership. This is in line with the intuition from our simple principal-agent model, where franchisee borrowing against their collateral to start their business increases their incentives to work hard and hence the profitability of franchising to the franchisors.

Other results are also in line with the intuition from our model. In particular, we find that the interest rate affects the attractiveness of franchising negatively. Since a higher interest rate normally would imply a higher repayment for given collateral, an increase in the interest rate increases the likelihood of defaulting, which leads to reduced incentives for the franchisee and hence a lower value of franchising to the franchisor. Similarly, when the amount to be borrowed goes up, the same intuition applies and franchising becomes less appealing to a chain. This explains the negative effect of required capital on the relative profitability of franchising.

Population affects the number of potential franchisees. In line with the intuition provided by our theoretical principal-agent model, population thus has a positive effect on the relative profitability of a franchised outlet. In addition, we use the amount of labor needed in a typical chain outlet to measure the importance of the manager's effort. While the estimate of its effect is statistically insignificant, we find a statistically significant positive effect for its interaction with collateralizable wealth. To understand the magnitude of the effect of this interaction term, we simulate the effect of a 30% decline in collateralizable housing wealth in all state/years for a typical firm with 1

Table 2: Estimation Results

	parameter	standard error
Log of opportunity arrival rate		
constant	3.001***	0.014
std. dev.	1.360***	0.024
Profitability of a company-owned outlet		
constant	-3.491***	0.038
population	0.287***	0.004
per-capita state product	0.010***	0.001
collateralizable housing wealth	-0.067***	0.006
Relative profitability of a franchised outlet		
collateralizable housing wealth	0.181***	0.006
interest rate	-0.088***	0.002
capital needed	-0.369***	0.012
population	0.003***	0.001
employees	-0.002	0.002
(coll. housing wealth)×(employees)	0.011***	0.0004
business products & services	-0.024	0.041
restaurant	0.159***	0.049
home services	1.055***	0.056
go to services	0.354***	0.053
auto; repair	0.703***	0.063
constant (retailer)	2.098***	0.055
std. dev.	2.264***	0.024
Outlet exit rate	0.305***	0.001
Log of entry cost		
mean	2.817***	0.163
std. dev.	0.497***	0.166
Probability of thinking of franchising		
when starting in business	0.152***	0.020
in subsequent years	0.179***	0.014

*** indicates 99% level of significance.

employee and for a typical firm with 10 employees.[17] (The standard deviation of the number of employees in the data is 7.79.) We find that a 30% decline in collateralizable housing wealth leads to a 16.7% drop in the number of outlets five years after the firm starts its business for a typical firm with 1 employee, and a 19.8% drop when the number of employees is 10. The effects on the number of outlets ten years after the firm starts its business are -18.9% and -22.5% for these two firms respectively. Since hiring and managing labor are a major part of what local managers do, these larger effects for types of businesses that use more labor are consistent with the implication that franchisee incentives arising from having more collateral at stake are particularly valuable in

[17]In this simulation, we set the value of all covariates, except "employees," at their average level.

businesses where the manager's role is more important to the success of the business. This again demonstrates the incentive channel through which potential franchisees' financial constraints affect the franchisors' growth. Similarly, the coefficients for the sector dummy variables suggest that, controlling for the level of labor and capital needed , the benefit of franchising is greatest for home services and auto repair shops, i.e., that these types of businesses are particularly well suited to having an owner operator, rather than a hired manager, on site to supervise workers and oversee operations more generally.

We also find a large and highly significant rate of closure of outlets in our data. Our estimate implies that about 31% of all outlets close every year. This is larger than the 15% exit rate documented in Jarmin, Klimek and Miranda (2009) for single retail establishments and 26% found by Parsa, Self, Njite and King (2005) for restaurants. We expect some of the differences in our estimate arises because our data comprises mostly new franchised chains in their first years in franchising. Two things happen to these chains that can explain our high exit rate. First, many of them are experimenting and developing their concept while opening establishments. Some of this experimentation will not pan out, resulting in a number of establishments being closed down. Second, when chains begin to franchise, they sometimes transform some of the outlets they had established earlier as company outlets into franchised outlets. In our outlet counts, such transfers would show up as an increase in the number of franchised outlets, combined with a reduction, and thus exit, of a number of company-owned outlets.

Finally, according to our estimates, only a fraction of the chains in our data are aware or thinking of franchising from the time they start in business. The majority of them, namely (100%-15%), or 85%, do not think of franchising in their first year in business.[18] The probability that they become aware or start thinking about franchising the next year or the years after that is larger, at 18% each year. The estimated average entry cost – the cost of starting to franchise – is 18.93 ($= e^{2.817+0.497^2/2}$). According to our estimates, this is about 11 times the average value of franchised outlets that the chains choose to open.[19] In the data, on average, seven franchised outlets are opened in the first year when a chain starts franchising, and seventeen are opened in the first two years in franchising. So, it takes on average between one and two years for a chain to grow eleven franchised outlets to recoup the sunk cost of entering into franchising.

To see how well our estimated model fits the entry and the expansion patterns of the chains in the data, we compare the observed distribution of the waiting time – left panel of Figure 5(a) – to the same distribution predicted by the model *conditional on* a chain having started franchising

[18]Note that around 17% of chains in our data start franchising right away, which is greater than our estimate of 15% who are aware of franchising when they start their business. This discrepancy arises because the observed proportion is conditional on starting to franchise by 2006.

[19]The value of an opened franchised outlet is $E(\pi_{fi\tau}|\pi_{fi\tau} > \pi_{ci\tau}$ and $\pi_{fi\tau} > 0)$. It is 1.75 on average (across chain/years) according to our estimates, which is about 1/11 of the estimated costs of entering into franchising. This finding is in line with the estimates in some case studies (see, for example, Grossmann (2013)).

by 2006. Since a chain is included in our data only after it starts franchising and the last year of our sample is 2006, this conditional distribution is the model counterpart of the distribution in the data. We make a similar comparison for the distributions of the number of company-owned and franchised outlets in Figures 5(b) and 5(c), respectively.[20] In all cases, our estimated model fits the data reasonably well. Figure 5(b) shows that the model over-predicts the fraction of chain/years with no company-owned outlet while also under-predicting the fraction of observations with one company-owned outlet, such that the sum is predicted rather well. We believe this occurs because our model does not capture the chain's desire to keep at least one company-owned outlet as a showcase for potential franchisees and a place to experiment with new products, for example. The figures also show, not surprisingly, that the distributions predicted by the model are smoother than those in the data.

In Online Appendix C, we simulate the distribution of the number of company-owned and franchised outlets when the decision on the timing of entry into franchising is taken as exogenous, i.e., the selection issue is ignored. In this case, the simulation underestimates the number of franchised outlets quite a bit. In particular, it over predicts the percentage of observations with zero franchised outlet by 12%. This is because ignoring selection means that we draw the unobservable profitability of a franchised outlet from the unconditional distribution so that, even when the draw is so small that the chain should not have started franchising, the simulated number of franchised outlets corresponding to this draw, which is most likely to be very small, is included when we compute the distribution of the predicted number of franchised outlets.

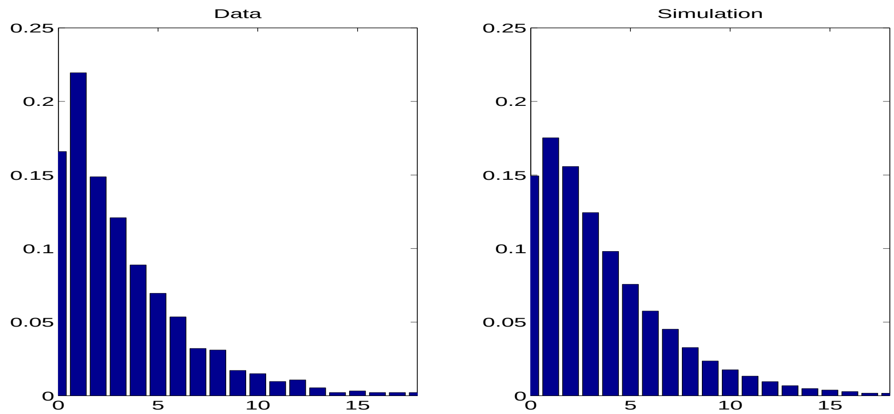
4.2 Robustness

Our theoretical and empirical model focus on the effect of collateralizable housing wealth on franchise chain decisions. In that context, they way in which we link the chain and macroeconomic variables is a particularly important consideration. To alleviate potential concerns that our results might be too dependent on the specific way in which did this, we estimate our model also using a different weight matrix. This alternative weight matrix incorporates the most information we have concerning the chains' expansion, namely, it uses data on the proportion of each chain's outlets in its top three states (three states where it has the most outlets). The construction of this weight matrix is described further, and the actual matrix is also shown, in Appendix A.4. The estimation results, in Table 3, show that using the alternative weight matrix yields results that are very similar to those we presented above. In terms of our main variable of interest, moreover, we find a coefficient for collateralizable wealth that is even larger than in our baseline specification. We conclude that our results are robust to reasonable variations in the way we link the macroeconomic data to our data on chains, and that our current baseline results provide relatively conservative estimates of the effects of interest.

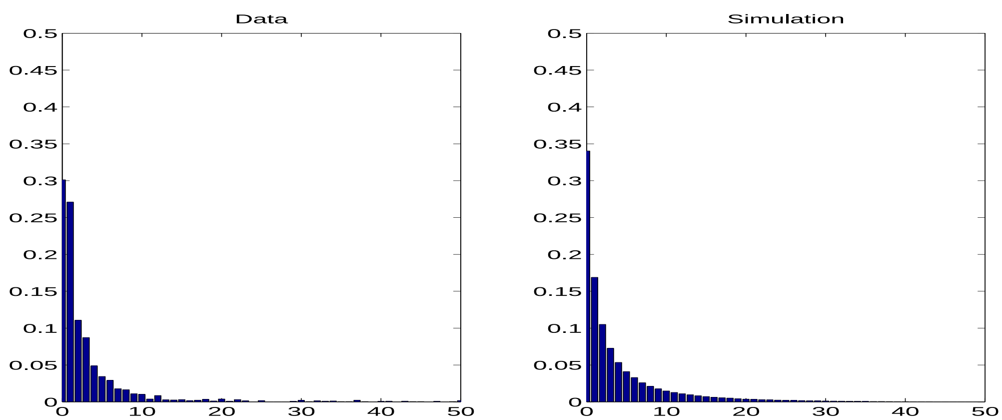
[20]Since there are only a few chain/years with more than 50 company-owned outlets, and more than 200 franchised

Figure 5: Fit of the Model

(a) Distribution of Waiting Time: Data vs. Simulation



(b) Distribution of the Number of Company-owned Outlets: Data vs. Simulation



(c) Distribution of the Number of Franchised Outlets: Data vs. Simulation

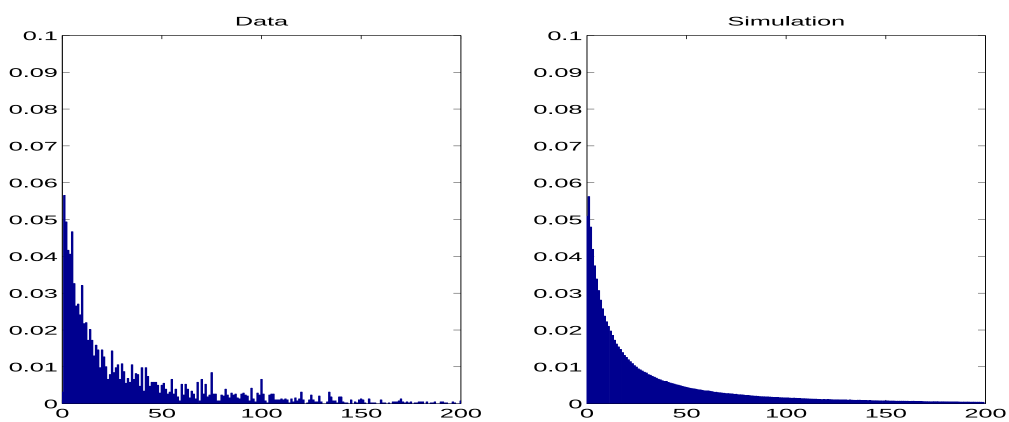


Table 3: Robustness Analysis: Different Weight Matrix to Link Chain-level and State-level Data

	parameter	standard error
Log of opportunity arrival rate		
constant	3.002***	0.014
std. dev.	1.347***	0.024
Profitability of a company-owned outlet		
constant	-3.511***	0.034
population	0.321***	0.005
per-capita state product	0.010***	0.001
collateralizable housing wealth	-0.075***	0.005
Relative profitability of a franchised outlet		
collateralizable housing wealth	0.208***	0.005
interest rate	-0.079***	0.002
capital needed	-0.335***	0.010
population	0.009***	0.001
employees	-0.002	0.003
(coll. housing wealth)×(employees)	0.009***	0.001
business products & services	-0.096**	0.042
restaurant	0.322***	0.046
home services	1.312***	0.078
go to services	0.434***	0.059
auto; repair	0.812***	0.072
constant (retailer)	1.589***	0.051
std. dev.	2.303***	0.026
Outlet exit rate	0.304***	0.001
Log of entry cost		
mean	2.855***	0.221
std. dev.	0.534**	0.261
Probability of thinking of franchising		
when starting in business	0.152***	0.021
in subsequent years	0.176***	0.014

*** indicates 99% level of significance.

** indicates 95% level of significance.

5 Assessing the Economic Importance of Collateralizable Housing Wealth

In this section, we use our baseline results to conduct a simulation where collateralizable housing wealth is decreased by 30% in all state/years in the data. This exercise helps us understand the economic magnitude of the estimated effect of collateralizable housing wealth on the extent of franchising and the expansion of the chains. A 30% decline in collateralizable housing wealth,

outlets, we truncate the graphs on the right at 50 and 200 respectively for readability.

moreover, is in line with the reduction in housing values that occurred in recent years, a period that lies outside our data period.[21]

To emphasize the incentive rather than the demand channel, we focus on results from a change in collateralizable wealth in the relative profitability of franchising only.[22] Figure 6 shows the distribution of the change in waiting time that results from this change in collateralizable wealth. For each chain/simulation draw, we compute the waiting time with and without a 30% decrease in local collateralizable housing wealth. We then compute the average waiting time across simulations for this chain.[23] The histogram of the average changes in waiting time, in Figure 6, shows that all chains in our data go into franchising on average (averaged over simulations) later with than without the change in franchisee financial constraints. The average effect of decreased collateralizable housing wealth on the chains' decisions to start franchising is 0.28 years. The average waiting time in the data is 3.15 years, so the average delay is about 9% of the average waiting time.

Figure 6: The Effect of Potential Franchisees' Financial Constraints on Chain's Waiting Time

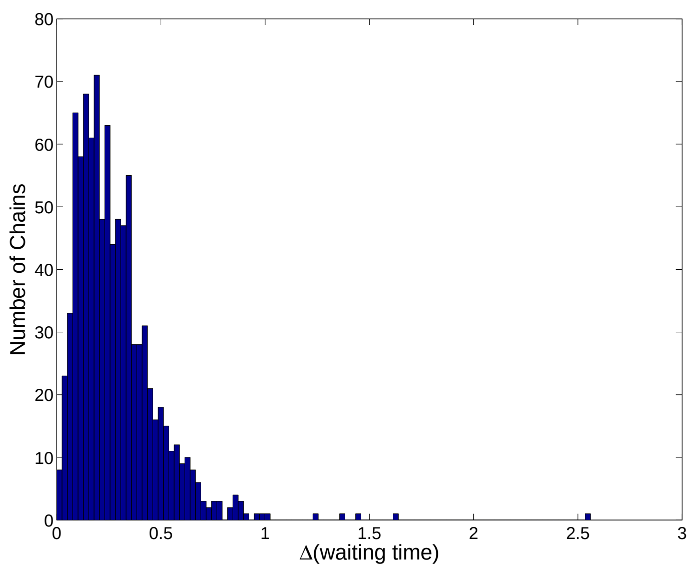


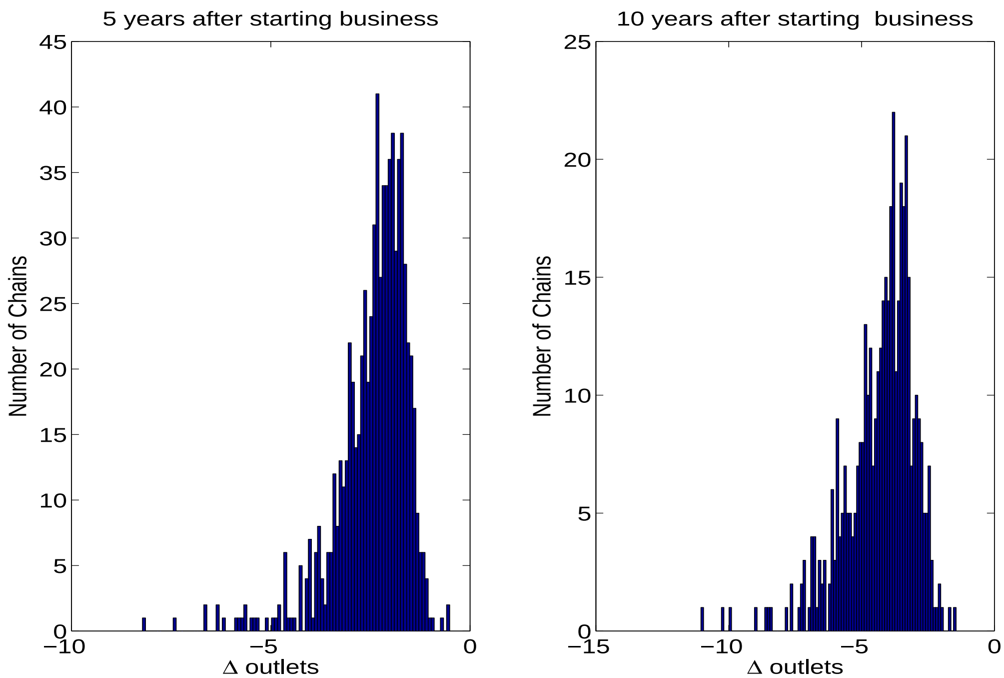
Figure 7 shows the average change in the number of outlets that results from the 30% decrease in potential franchisee collateralizable wealth. The results of our simulations imply that the number

[21]Median net worth fell 38.8 percent between 2007-2010 mostly because of the reduction in housing values (see Bricker, Kennickell, Moore and Sabelhaus (2012)). Since our data end in 2006, our estimates are obtained based on information that predates the U.S. housing crisis.

[22]Our estimation results imply that collateralizable housing wealth has a negative effect on the demand side. If we allow this channel to operate as well, we get lower net effects, in the order of 4% to 5% reductions in total number of outlets, instead of the 10% we report below. Of course, the results we report are the relevant ones for our purposes.

[23]We use the simulated distribution without the decrease in collateralizable housing wealth rather than the empirical distribution directly from the data as the benchmark for two reasons. First, we do not want estimation errors to contribute to the observed differences between the distributions with and without the decrease in collateralizable housing wealth. Second, since we are interested in the effect of tightening franchisee's financial constraints on waiting time, we need to plot the *unconditional* distribution of the waiting time, which is not observable in the data. In the data, we only observe the distribution conditional on entry into franchising before 2006.

Figure 7: The Effect of Potential Franchisees' Financial Constraints on the Number of Outlets



of total outlets of chains five years after they start in business decreases by 2.43.[24] This average is taken over simulations and 757 chains that appear in our sample in the fifth year after they start in business. In total, these 757 chains would fail to open 1840 outlets and 11,879 jobs in the process.[25] Similarly, there are 437 chains that appear in our sample in the tenth year after starting in business. Our simulation indicates that these chains would have 1875 fewer outlets ten years after starting in business, or 4.29 fewer outlets each on average. The direct corresponding job loss would be 13,319.

Of course, the franchised chains in the above simulation are only a subset of all franchisors. To understand what the overall impact of the tightening of franchisees' financial constraints might be, we can use the average percentage changes in the number of outlets five and ten years after a chain starts its business. They are, respectively, 10.11% and 10.27%. Per the Economic Census, business-format franchised chains had more than 380,000 establishments, and accounted for 6.4 million jobs in the U.S. in 2007. Using these figures, and the percentage changes in outlets that we obtain, the predicted number of jobs affected could be as large as 650,000. Of course, this is a partial equilibrium result for understanding the economic magnitude of the key estimated parameters. For example, we hold the number of employees in an outlet constant in the simulations. Yet this could

[24]The average number of outlets five years after a chain starts its business is 24.97 in the data. The simulated counterpart (without any change in collateralizable housing wealth) is 24.17.

[25]These numbers also are averaged over simulations. We can simulate the lack of job creation because we observe the typical number of employees needed in an outlet for each chain.

be a margin on which the chains would adjust. This number is rather constant within chains over time in our data, however, which is to be expected given the standardized business concepts that these chains emphasize. For another example, the lack of growth of franchised chains also might allow other firms to go into business. However, the financial constraints faced by franchisees has been touted as a major factor impeding the growth of small businesses generally. Hence it is not clear that the reduction in number of outlets we document could be made up by an increase in the number or growth of other businesses.

6 Conclusion

In this paper, we study how agents financial constraints affect principals' organizational choice decisions and growth in the context of franchising. We have shown theoretically and empirically that the entry of a chain into franchising and its growth via franchised and company-owned outlets are all intrinsically linked. We have also shown that these depend in a systematic way on the availability of financial resources for potential franchisees. The magnitude of the effects is sizable, suggesting that financial constraints play an important role for the type of small business owners that franchisors try to attract into their ranks. In other words, our results show that franchisees' investments in their businesses are an important component of the way franchisors organize their relationships with their franchisees. When the opportunities for such investments are constrained, franchising as a mode of organization becomes less efficient, and the chains rely on it less. This, in turn, reduces their growth rates and total output.

We view the incentive effect of collateralizable housing wealth that we emphasize as quite complementary to that of the residual claims that have been the typical focus of the agency literature. The reliance on franchisee collateralizable housing wealth gives strong incentives to franchisees in the early years of their business, a period during which profits, and hence residual claims, are small or even negative, but the amount of wealth put up in the business is most often at its maximum. Franchising thus provides an ideal setting to study the relationship between moral hazard and agent collateral.

From a methodological perspective, our data only show the net change in number of outlets each year. Nonetheless, we provides a framework to estimate the creation and exit of outlets separately, and we explain the information needed for identification. We view our empirical model as a step toward developing empirically tractable analyses of factors that principal-agent models suggest are important, but that are often difficult to capture empirically within the confines of what are often limited, and in our case, aggregated data on firm decisions. Authors often face similar data constraints in other contexts, and so we hope that our approach will provide some useful building blocks for them as well.

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Appendices

A Data Appendix

This appendix provides further details on data and measurement issues.

A.1 Franchisor Sample and Characteristics

We constructed our sample of franchised chains from yearly issues of the Entrepreneur Magazine from 1981 to 1993, and an annual listing called the *Bond Franchise Guide* (previously the *Source Book of Franchise Opportunities*) from 1994 to 2007. In each case, the publication is a year late relative to the year of data collection, so we obtain the 1980 to 1992 data from the first source and the 1993 to 2006 data from the second. Because the *Bond Franchise Guide* was not published in 2000 and 2003, we are missing data for all franchisors for 1999 and 2002.

Because our state-level macroeconomic variables of interest are only available from 1984 onward, we constrain our sample to U.S.-based franchisors that started in business in 1984 or later. This means that our sample comprises mostly young brands, with small number of establishments: well-known brands such as McDonald's and Burger King, for example, were established in the 1950s and 1960s. Our data sources provide information on 1016 such U.S.-based franchisors.

After eliminating hotel chains (for reasons given in footnote 4), and deleting observations for outlier franchisors who either grow very fast (the number of outlets increases by more than 100 in a year) or shrink very fast,[26] our final sample consists of 3820 observations regarding 934 distinct franchised chains, for an average of four observations per chain. This short duration for our panel is explained in part by the large amount of entry into and exit from franchising (or business) of the chains as well as the lack of data for 1999 and 2002.[27]

For each franchisor/year in our sample, we have data on the amount of capital required to open an outlet (Capital Required) and the number of employees that the typical outlet needs (Number of Employees). We transform the former to constant 1982-84 dollars using Consumer Price Index data from the Bureau of Labor Statistics. For the latter, we count part-time employees as equivalent to 0.5 of a full-time employee.

[26] A franchisor is considered shrinking very fast if more than half of the existing outlets exit in a year and the probability of such amount of exits be less than 1e-10 even when the exit rate of each outlet is as high as 50%. We impose the second criterion to avoid removing small chains for which a decrease in outlets from say 3 to 1 or 4 to 1 might well occur.

[27] See e.g. Blair and Lafontaine (2005) for more on the entry and exit rate of chains.

We view the Capital Required (in constant dollars) and the Number of Employees needed to run the business as intrinsically determined by the nature of the business concept, which itself is intrinsically connected to the brand name. So, they should not change from year to year. Yet we find some variation in the data. Since the data are collected via surveys, they are subject to some errors from respondents or transcription. We therefore use the average across all the observations we have for these two variables for each franchised chain under the presumption that most of the differences over time reflect noise in the type of survey data collected by our sources. There is also some variation in the reported years in which the chain begins franchising and when it starts in business. For these variables, we use the earliest date given because we see that franchisors sometimes revise these dates to more current values for reasons we do not fully understand. However, we make sure that the year of first franchising is after the first year in business. We also push the year of franchising to later if we have data indicating no franchised establishments in the years when the chain states it starts franchising.

A.2 Collateralizable Housing Wealth

We measure collateralizable housing wealth using

- data on a yearly housing price index at the state level from the Federal Housing Finance Agency. These data are revised at the source quite frequently, perhaps as often as every time a new quarter is added. They also have been moved around several web sites. The version used here is the "States through 2010Q3 (Not Seasonally Adjusted) [TXT/CSV]" series in the All-Transactions Indexes section at http://www.fhfa.gov/Default.aspx?Page=87. The base period of the index is 1980Q1;

- data on housing values by state in 1980 from the Census Bureau (the base year of the aforementioned housing price index). These data are in constant year 2000 based dollars. We transform them to constant 1983-84 based constant dollars using the Consumer Price Index.

The combination of the above two sets of data allows us to generate time series of yearly housing values per state, from 1980 onward. We then complement these with the following:

- yearly data about home ownership rates across states from the Census Bureau's Housing and Household Economic Statistics Division;

- data from the joint Census-Housing and Urban Development (HUD) biennial reports, based on the American Housing Surveys, which summarize information on mortgages on a regional basis (Northeast, Midwest, South and West). Specifically, from this source, we obtained measures of regional housing values, total outstanding principal amount, and number of houses owned free and clear of any mortgage (Tables 3-14 and 3-15 of the biennial reports).

The data for housing values and for total outstanding principal are reported in the form of frequencies for ranges of values. We use the middle value for each range and the frequencies to calculate expected values for these. We then combine these data to calculate the average proportion of mortgage outstanding for homeowners in the region each year. Specifically, we calculate $\frac{\frac{(TOPA*NTOPA)}{(NTOPA+NF)}}{(HousingValues)}$, where TOPA is Total Outstanding Principal Amount, NTOPA is the Number of households that reported Total Outstanding Principal Amount, and NF is the Number of households with houses owned Free and clear of any mortgage. Since the data on TOPA, NTOPA, and NF are by region, we ascribe the regional expected value to all states in the region.[28] Also, since the joint Census-Housing and Urban Development (HUD) reports are biennial, we ascribe the value to the year of, and to the year before, the report. This means that we can generate our main explanatory variable of interest below from 1984 onward.

In the end, we combine the information on the proportion of outstanding mortgage for homeowners (data in the fourth item above) with the state home ownership rate (the third item) and housing value time series (combination of the first and the second items) to calculate our measure of Collateralizable Housing Wealth for each state/year, given by: (1− the average proportion of mortgage still owed) ×(the home ownership rate)×(housing value).

A.3 Other Macroeconomic Variables

Real Gross State Product (GSP) data are from the Bureau of Economic Analysis. We deflate nominal annual GSP data using the Consumer Price Index also from the Bureau of Labor Statistics, and obtain per capita GSP after dividing by population. The annual population data are from the Census Bureau. The interest rate data series we use is the effective Federal Funds rate annual data (downloaded from the Federal Reserve web site, at http://www.federalreserve.gov/releases/h15/data.htm on 03/26/2009), in percent.

A.4 Weighing Matrices

As described in the body of the paper, we create our main weighing matrix using information from the 1049 franchisors in our data that we observe at least once within 15 years after they start franchising. We use only one year of data per franchisor, namely the latest year within this 15 year period, to construct the matrix. For each state pair (s_1, s_2), the weight is defined as $\sum_{j \in J_{s_1}} \mathbb{1}\,(s_2 \text{ is the top state for chain } j)\,/\#\,(J_{s_1})$, where J_{s_1} is the set of chains that are headquartered in state s_1, $\#(J_{s_1})$ is the cardinality of the set J_{s_1}, and $\mathbb{1}\,(s_2 \text{ is the top state for chain } j)$ is

[28] We investigated several other data sources for home equity and housing values, some of which provide data at a more disaggregated level. However, none of them allowed us to go back in time as far as 1984, as our current sources do. Moreover, these sources most often covered a number of major cities but did not provide state-level data.

a dummy variable capturing whether chain j reports s_2 as the state where they have the most outlets. In other words, the weight is the proportion of chains headquartered in s_1 that report s_2 as the state where they have the most outlets. The resulting matrix is shown below as Matrix A.

We use an alternative set of weights in our robustness analysis. Our data source identifies three (or two, or one if there are only two or one) U.S. states where the chain has the most outlets, and for each of those, it states how many outlets it has. Our alternative weighing matrix takes all these into account, namely it uses data from all top three states (as opposed to only the top state in Matrix A) as well as the relative importance of these top three states, in the form of the proportion of outlets in each state relative to the total in all three (as opposed to only using a dummy to capture whether a state is the top state as in Matrix A). Specifically, for each chain j, we calculate $N_j = n_{1j} + n_{2j} + n_{3j}$, where n_{kj} is the number of establishments of the chain in its top three states $k = 1, 2$ or 3. We then calculate $p_{kj} = n_{kj}/N_j$. For each state pair (s_1, s_2), we calculate the average proportion of establishments in origin state s_1 and destination state s_2 pair across all the chains headquartered in state s_1 as $\sum_{j \in J_{s_1}} [p_{1j} \mathbb{1}(s_2$ is franchisor j's state with the most outlets$) + p_{2j} \mathbb{1}(s_2$ is franchisor j's state with the second most outlets$) + p_{3j} \mathbb{1}(s_2$ is franchisor j's state with the third most outlets$)] / \#\left(J_{s_1}\right)$. Note that the sum of these average proportions across destination states s_2 for each origin state s_1 is again 1.

The resulting matrix is shown below as Matrix B. As can be seen from a comparison of the matrices, the matrix we rely on in our main specification (Matrix A) allocates some weight to macro conditions outside of the chain's headquarters state, but not as much as Matrix B does. The latter is a little more dispersed. Overall, the two matrices are similar. Consequently, per the descriptive statistics in Table A.1, the weighted macroeconomic variables are similar as well. Compared to using the macroeconomic variables of the home state only, with no weights, the mean and standard deviation of population in particular is quite different once we apply our weights. It is therefore important that we use these weighing matrices as this allows variation in the economic conditions of other relevant states to affect the decisions of chains headquartered in typically smaller, lower collateralizable housing wealth states.

Table A.1: Summary Statistics for Macroeconomic Variables for Different Weight Matrices: At the state/year level, for 48 states between 1984 and 2006

	Mean	Median	S.D.	Min	Max	Obs
No Weights						
Coll. Housing Wealth (82-84 $10K)	3.41	3.03	1.52	1.51	14.17	1104
Population (Million)	5.46	3.83	5.83	0.52	36.12	1104
Per-Capita Gross State Product (82-84 $10K)	1.85	1.73	0.67	1.09	7.47	1104
Main Matrix (Matrix A)						
Coll. Housing Wealth (82-84 $10K)	3.62	3.34	1.31	1.83	14.17	1104
Population (Million)	8.84	8.23	5.52	0.52	31.68	1104
Per-Capita Gross State Product (82-84 $10K)	1.89	1.79	0.63	1.22	7.47	1104
Alternative Matrix (Matrix B)						
Coll. Housing Wealth (82-84 $10K)	3.61	3.28	1.17	2.11	13.21	1104
Population (Million)	8.67	8.20	4.73	1.14	28.92	1104
Per-Capita Gross State Product (82-84 $10K)	1.89	1.80	0.54	1.26	6.60	1104

B Details on the Parametric Model in Section 3.2

In this Appendix, we describe the parametric model for our analysis in Section 3.2. In this parametric model, we assume a linear revenue function $G(\theta, a) = \theta + \lambda a$. The profit shock θ follows a normal distribution with mean 6 and a variance of 9. Opening an outlet in this chain requires capital $I = 5$. In the debt contract, the repayment R depends on the amount of money borrowed (I) and the collateral (C) according to the following linear function: $R = (1 + r) I$ where $r = 0.35 - (0.35 - 0.01)C/I$. In other words, the interest rate is 35% when $C = 0$ and 1% when $C = I$.

The franchisee's utility function is $-e^{-\rho w}$ where $\rho = 0.005$ is her parameter of absolute risk aversion and w is her payoff. It is costly for her to exert effort. The cost is $\Psi(a) = e^{a}$.

We assume that the number of potential franchisees N follows a Poisson distribution with mean $\bar{N}$. The collateralizable wealth that each potential franchisee has follows a truncated normal distribution with mean $\bar{C}$ and a variance of 1. It is truncated on the left at 0.

The expected profit from a company-owned outlet is $\tilde{\pi}_c = E_\theta [G(\theta, a_0) \mathbb{1}(G(\theta, a_0) > 0)] - I$. We normalize the hired manager's effort a_0 to be 0 and the corresponding compensation to be 0. Thus, $\tilde{\pi}_c = 1$ in our example.

Matrix A: The Main Weighing Matrix Used in Constructing Values for Macroeconomic Variables Relevant to each Chain

	AK	AL	AR	AZ	CA	CO	CT	DC	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY	sum
AL	0	0.63	0	0	0	0	0	0	0	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13	0	0	0	0	0	0	0	0	0	0	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AR	0.09	0	0.45	0	0	0.09	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0.27	0	0	0	0	0	0	0	1
AZ	0	0	0	0.42	0.35	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.06	0	0	0	0	0	0	0	0.03	0.03	0	0	0	0	0.03	0	0	1
CA	0	0	0	0.01	0.82	0.02	0	0	0	0.02	0.01	0	0	0	0	0	0	0.01	0	0	0	0	0.02	0.01	0.01	0	0	0.01	0	0	0	0	0	0.01	0.01	0.01	0	0.01	0	0	0	0	0.01	0.03	0	0	0	0.01	0	0	0	1
CO	0	0	0	0	0.17	0.65	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0.02	0.06	0	0	0	0	0	0	0	1
CT	0	0	0	0	0	0	0.71	0	0	0	0.05	0	0	0	0	0	0	0	0	0.10	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
DC	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
DE	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0	0	0	0	0	0	0	0	1
FL	0	0	0	0	0.14	0.01	0.01	0.01	0	0.62	0.03	0	0	0	0	0	0	0.01	0	0.01	0	0	0	0.01	0	0	0	0.01	0	0	0	0.02	0	0	0.04	0.01	0	0.01	0.01	0	0	0	0	0.06	0	0	0	0	0	0	0	1
GA	0	0.02	0	0	0.10	0	0	0	0	0.18	0.38	0.02	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	0	0.07	0	0	0	0.02	0	0	0.02	0.02	0	0.02	0.02	0	0.03	0	0.02	0.08	0	0	0	0	0	0	0	1
HI	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
IA	0	0	0	0	0	0	0	0	0	0.11	0	0	0.78	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ID	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
IL	0	0	0	0	0.11	0	0	0	0	0.02	0	0	0	0	0.64	0.02	0	0	0	0	0	0	0.05	0.02	0	0	0	0	0	0	0	0.02	0	0	0	0.07	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	1
IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0.55	0	0.09	0	0	0	0	0.09	0	0	0	0	0	0	0	0	0	0	0	0	0.18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
KS	0	0	0	0	0	0	0	0	0	0.07	0	0	0.07	0	0	0	0.33	0	0	0	0	0	0	0.07	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.07	0.20	0	0	0	0	0.07	0	0	1
KY	0	0	0	0	0	0	0	0	0	0.11	0	0	0	0	0	0.06	0	0.61	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0.06	0	0	0	0	0	0	0	0.06	0	0	0	0	0.06	0	0	1
LA	0	0	0.06	0	0.06	0	0	0	0	0	0	0	0	0.06	0	0	0	0	0.56	0	0	0	0	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13	0	0.06	0	0	0	0	0	1
MA	0	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.74	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0	0.04	0	0	0	0	0.04	0	0	0	0.09	0	0	0	0	0	0	0	1
MD	0	0	0	0	0.17	0	0	0	0	0.10	0	0	0	0	0	0	0.03	0	0	0	0.47	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0	0	0.03	0	0	0	0	0.03	0	0.07	0	0	0.03	0	0	1
ME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
MI	0	0	0	0	0.08	0	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0.02	0	0	0.80	0	0	0	0	0	0	0	0	0.02	0	0	0	0.02	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	1
MN	0	0	0	0.04	0.08	0	0.02	0	0	0.04	0	0	0.02	0	0.02	0	0	0	0	0	0	0	0	0.54	0	0	0	0.02	0	0.04	0	0	0	0	0	0.10	0	0.02	0.02	0	0	0	0	0	0	0	0	0	0.04	0	0	1
MO	0	0	0	0	0	0	0	0	0	0.10	0	0	0.05	0	0.05	0	0.10	0	0	0	0	0	0	0	0.52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0.14	0	0	0	0	0	0	0	1
MS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.33	0	0	0	1
MT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
NC	0	0	0	0	0.05	0	0	0	0	0.11	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0.50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
NE	0	0	0	0	0.14	0	0	0	0	0.03	0	0	0.03	0	0.03	0	0.03	0	0	0	0	0	0.03	0	0	0	0	0	0	0.52	0	0	0	0	0	0.03	0	0	0	0	0	0	0	0.07	0	0.03	0	0	0.03	0	0	1
NH	0	0	0	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
NJ	0	0	0	0	0.09	0	0	0	0	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	0	0.55	0	0	0.09	0.02	0	0	0.09	0	0	0	0.02	0.02	0	0.02	0	0	0	0	0	1
NV	0	0	0	0	0.21	0.07	0	0	0	0.07	0	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.14	0	0	0	0	0	0.14	0	0	0	0	0	0	0	0	0	0	0	0.07	0	0.21	0	0	0	1
NY	0	0	0	0	0.06	0	0.04	0	0	0.08	0.04	0.02	0	0.02	0	0	0	0.02	0	0.02	0	0	0.02	0	0	0	0	0	0	0	0	0.04	0	0	0.59	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0	1
OH	0	0	0	0	0.11	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0	0	0.03	0	0.03	0	0	0	0	0.02	0	0	0	0.02	0	0	0	0.68	0	0	0.02	0	0	0	0.02	0.03	0.02	0	0	0	0	0	0	1
OK	0	0	0	0	0	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0.08	0	0	0	0.08	0.50	0	0	0	0	0	0	0	1
OR	0	0	0	0.05	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.62	0	0	0	0	0	0	0	0	0	0.24	0	0	0	1
PA	0	0	0	0	0.02	0	0	0	0.02	0.05	0.02	0	0	0	0.02	0	0	0.02	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0.07	0	0	0	0.63	0	0.02	0	0	0.05	0	0	0	0	0	0.02	0	1
RI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0	0	0	0	0	0	0	0	0	1
SC	0	0	0	0	0.11	0	0	0	0	0.11	0	0	0	0	0	0	0	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0	0	0	0.11	0	0	0	0	0.44	0	0	0	0	0	0	0	0	0	0	1
SD	0	0	0	0	0	0	0	0	0	0.10	0	0	0.10	0	0	0	0	0	0	0	0	0	0	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.70	0	0	0	0	0	0	0	0	0	1
TN	0	0.04	0.04	0	0.11	0	0	0	0	0.04	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.50	0.04	0	0.04	0	0	0	0	0	1
TX	0	0	0	0.02	0.18	0	0	0	0	0.02	0.02	0	0	0	0.01	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0	0.02	0.01	0.01	0	0	0	0	0	0	0	0.01	0.68	0	0.01	0	0	0	0	0	1
UT	0	0	0	0	0.52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0	0	0	0	0	0.04	0.35	0	0	0	0	0	0	1
VA	0	0	0	0	0.13	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0	0.04	0	0	0	0	0	0	0.09	0.04	0	0	0.09	0	0	0	0	0	0	0.52	0	0	0	0	0	1
VT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	1
WA	0	0	0	0	0.06	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.12	0	0	0	0	0	0.06	0	0	0	0.71	0	0	0	1
WI	0	0	0	0	0.08	0	0	0	0	0.08	0	0	0	0	0.08	0	0	0	0	0	0	0	0.08	0.04	0	0	0	0	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0.58	0	0	1
WV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.20	0	0	0.20	0	0	0	0	0	0	0	0	0	0	0.40	0	1

For a chain whose home state is AL, for example, its macroeconomic variable is the weighted sum of the macroeconomic variable in the 51 states where the weights are given by the first row.
Weights larger than or equal to 0.10 are highlighted.

Matrix B: Alternative Weighing Matrix Used in Constructing Values for Macroeconomic Variables Relevant to each Chain

	AK	AL	AR	AZ	CA	CO	CT	DC	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY	sum
AL	0	0.35	0	0	0	0	0	0	0	0.14	0.05	0	0	0	0	0	0	0	0.02	0	0	0	0	0.06	0	0	0	0.01	0	0	0	0	0	0	0.05	0.05	0	0	0	0	0.00	0	0.19	0	0	0.05	0	0	0.01	0	0	1
AR	0.02	0	0.33	0.04	0.05	0.08	0	0	0	0.01	0	0	0	0	0	0.02	0.00	0	0.01	0	0	0	0	0	0.04	0	0	0	0	0.01	0	0	0	0	0	0	0.01	0	0	0	0	0	0.09	0.28	0	0	0	0	0	0	0	1
AZ	0	0	0	0.38	0.20	0.03	0	0.01	0	0.06	0	0	0	0	0	0	0	0	0	0	0.00	0.00	0	0	0	0	0	0.00	0	0.01	0	0.01	0	0.00	0.08	0.01	0	0.00	0.00	0	0	0	0.02	0.07	0.02	0.01	0	0.01	0.04	0	0	1
CA	0	0.00	0	0.02	0.71	0.02	0	0	0	0.02	0.02	0.00	0	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0	0.00	0.01	0.00	0.00	0	0.00	0	0.00	0.00	0.01	0.00	0.01	0.02	0.01	0.00	0.01	0.01	0	0	0	0.00	0.04	0.00	0	0	0.02	0.00	0	0	1
CO	0	0	0	0.03	0.11	0.49	0	0	0	0.12	0.01	0.00	0.01	0.02	0.01	0	0.00	0	0	0	0	0	0.00	0.00	0.04	0	0.00	0.01	0	0	0.00	0	0	0.00	0.00	0.01	0	0	0.00	0	0.00	0.01	0.01	0.08	0.01	0.00	0	0.01	0.00	0	0	1
CT	0	0	0	0	0	0.01	0.63	0	0.01	0.02	0.02	0	0	0	0	0	0	0	0	0.10	0.01	0	0.01	0	0	0	0	0	0	0	0.01	0.06	0.00	0	0.08	0.00	0	0	0.01	0	0.01	0	0	0.01	0	0.00	0	0	0	0.01	0	1
DC	0	0	0	0	0	0	0	0.83	0	0	0	0	0	0	0.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
DE	0	0	0	0	0	0	0	0	0.37	0	0	0	0	0	0	0	0	0	0	0	0.19	0	0	0	0	0	0	0	0	0	0	0.08	0	0	0	0	0	0	0.36	0	0	0	0	0	0	0	0	0	0	0	0	1
FL	0	0.01	0.00	0.00	0.09	0.01	0.00	0.01	0	0.52	0.04	0	0	0	0.02	0	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0	0.02	0	0.00	0	0.03	0	0.00	0.04	0.02	0	0.01	0.02	0.00	0.01	0	0.00	0.08	0.00	0.01	0	0.01	0.00	0.00	0	1
GA	0	0.04	0.00	0	0.08	0.01	0	0	0	0.12	0.32	0.03	0	0	0.02	0	0	0.00	0.01	0.00	0.01	0	0.01	0.00	0	0	0	0.07	0	0	0	0.01	0	0	0.03	0.03	0.00	0.02	0.02	0	0.02	0	0.03	0.10	0	0.01	0	0	0.00	0	0	1
HI	0	0.08	0	0	0	0	0	0	0	0	0	0.92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
IA	0	0	0	0	0.01	0.01	0	0	0	0.04	0	0	0.49	0	0.19	0.01	0	0	0	0	0	0	0.07	0.08	0.02	0	0	0	0	0.01	0	0	0	0	0	0.01	0	0	0	0	0	0.02	0	0	0.02	0	0	0	0.02	0	0	1
ID	0	0	0	0.01	0	0.04	0	0	0	0	0	0	0	0.38	0	0	0.02	0	0	0	0	0	0	0	0	0	0.33	0	0.01	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0	0	0.09	0	0	0	1
IL	0.00	0.00	0	0.00	0.07	0	0	0	0	0.06	0.00	0	0.01	0	0.50	0.03	0	0	0	0.01	0	0	0.08	0.01	0.00	0	0	0	0	0	0	0.02	0	0	0	0.06	0.01	0	0.03	0	0.00	0	0.01	0.04	0	0.00	0	0.01	0.05	0	0	1
IN	0	0	0	0	0	0	0	0	0	0.01	0	0	0	0	0.09	0.56	0	0.13	0	0.01	0	0	0.06	0.05	0	0	0	0	0	0	0	0	0	0	0.01	0.08	0	0	0	0	0	0	0	0.00	0	0	0	0	0	0	0	1
KS	0	0	0	0.01	0.03	0.01	0	0	0	0.02	0.01	0	0.02	0	0.05	0	0.29	0	0	0	0	0	0	0.04	0.21	0	0	0.00	0	0.01	0	0	0	0.00	0.01	0.01	0.03	0	0	0	0	0	0.03	0.23	0	0	0	0	0.01	0	0	1
KY	0	0	0	0	0.05	0.01	0.03	0	0	0.11	0	0	0	0	0.02	0.09	0	0.47	0	0	0.02	0	0.03	0	0	0	0	0	0	0	0	0.01	0	0	0.03	0.02	0	0	0	0	0	0	0.07	0.01	0	0	0	0	0.03	0	0	1
LA	0	0.04	0.07	0	0.05	0	0	0	0	0.05	0	0	0	0.01	0.01	0	0	0	0.43	0.01	0	0	0	0	0	0.00	0	0.08	0	0	0	0.01	0	0	0	0	0	0	0.01	0	0.03	0	0.01	0.08	0	0.08	0	0.01	0	0	0	1
MA	0	0	0	0	0.02	0	0.05	0	0	0.04	0	0	0	0	0.01	0.00	0	0	0	0.59	0.01	0	0	0	0	0	0	0.01	0	0	0.03	0.04	0	0	0.06	0.03	0	0	0	0.03	0	0	0	0.08	0	0	0	0	0	0	0	1
MD	0	0.00	0	0	0.05	0.01	0	0.01	0	0.03	0.03	0	0	0	0.01	0	0.02	0	0	0.01	0.39	0	0.01	0	0.01	0	0	0	0	0	0	0.05	0	0.00	0.01	0.01	0	0.00	0.10	0	0	0	0	0.05	0.00	0.15	0	0	0.04	0	0	1
ME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.92	0	0	0	0	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
MI	0	0.01	0	0	0.06	0.00	0	0	0	0.05	0	0	0	0	0.01	0.01	0	0	0.01	0.01	0.00	0	0.71	0.01	0.00	0	0	0.00	0	0	0.00	0.02	0	0.00	0.00	0.04	0	0	0.01	0	0.00	0	0	0.05	0	0.00	0	0	0.00	0	0	1
MN	0	0.00	0	0.02	0.05	0.03	0.00	0	0.00	0.02	0.01	0	0.03	0	0.05	0.02	0.00	0	0	0	0.01	0	0.02	0.46	0.01	0	0	0.01	0.00	0.02	0.00	0.00	0	0	0	0.08	0	0.00	0.02	0	0	0	0.00	0.02	0	0.01	0	0.02	0.07	0	0	1
MO	0	0	0	0	0.02	0.03	0.01	0	0	0.02	0.01	0	0.06	0	0.11	0.01	0.06	0	0	0.00	0	0	0.01	0.00	0.47	0	0	0	0	0.00	0	0	0	0	0.01	0.06	0	0	0.01	0	0.01	0	0.01	0.08	0	0	0	0	0	0	0	1
MS	0	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.43	0	0	0	0	0	0	0	0	0	0	0.10	0	0.14	0	0	0	0.07	0	0	0	0	0.19	0	0	0	1
MT	0	0	0	0	0	0	0	0	0	0.12	0	0	0	0.09	0	0	0	0	0	0	0	0	0	0	0	0	0.65	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.07	0	0	0.07	0	0	0	1
NC	0	0	0	0	0.03	0	0	0	0	0.08	0.09	0	0.01	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0.56	0	0	0	0.02	0	0	0.02	0.01	0	0	0.00	0	0.08	0	0.01	0.01	0	0.04	0	0	0	0	0	1
ND	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0	0	0	0	0	0	0	0	0	0	0.57	0	0	0	0	0.24	0	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0	0	0	0	0	0.04	0	0	1
NE	0	0	0	0	0.11	0.03	0	0	0	0.07	0.01	0	0.04	0	0.04	0.01	0.03	0	0	0	0.01	0	0.02	0.03	0.01	0	0	0	0	0.43	0	0	0	0	0.03	0.01	0	0	0.01	0	0	0	0	0.07	0	0.01	0.01	0	0.04	0	0	1
NH	0	0	0	0	0	0.11	0.18	0	0	0.18	0	0	0	0	0	0	0	0	0	0.23	0	0	0	0	0	0	0	0	0	0	0.18	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0	0	0	0	0	0	0	1
NJ	0	0	0	0	0.09	0.02	0.02	0	0	0.05	0.00	0	0	0	0	0	0	0	0	0.02	0.01	0	0.01	0	0.00	0	0	0.02	0	0	0	0.42	0.01	0	0.08	0.01	0	0.01	0.13	0	0.01	0	0.01	0.06	0	0.01	0	0.01	0	0	0	1
NV	0	0	0	0	0.25	0.03	0	0	0	0.03	0	0.02	0	0	0.03	0.01	0	0	0	0.01	0	0	0	0	0	0	0	0.03	0	0	0	0	0.03	0.12	0.05	0.01	0.03	0	0.06	0	0	0	0	0.01	0	0.02	0	0.26	0	0	0	1
NY	0	0	0	0	0.06	0	0.05	0	0	0.02	0.03	0.01	0	0.00	0.01	0	0	0.01	0.01	0.02	0.00	0	0.01	0	0	0	0	0.02	0	0	0	0.06	0	0	0.55	0.02	0	0	0.06	0	0	0	0.02	0.02	0	0.01	0.01	0.01	0	0	0.01	1
OH	0	0	0.00	0.00	0.07	0.01	0	0	0	0.05	0.01	0	0	0	0.03	0.03	0.01	0.03	0	0.00	0.01	0	0.06	0	0.01	0.01	0	0.01	0	0	0	0.01	0	0	0.00	0.54	0	0	0.03	0	0	0	0.03	0.03	0.01	0.00	0	0	0	0.00	0	1
OK	0	0	0	0	0.08	0	0	0	0	0.17	0.01	0	0	0	0.02	0	0.01	0	0	0	0	0	0	0	0	0	0	0.01	0	0.03	0	0	0	0	0	0.01	0.16	0.01	0.01	0	0	0	0.02	0.43	0	0	0	0.04	0	0	0	1
OR	0	0	0	0.01	0.06	0.00	0	0	0	0.01	0	0.00	0	0.02	0	0.00	0	0	0	0	0	0	0	0	0	0	0	0.01	0.00	0	0	0	0	0.01	0	0	0	0.62	0	0	0	0	0.00	0.02	0	0.00	0	0.22	0	0	0	1
PA	0	0.01	0	0.01	0.03	0.01	0.01	0	0.03	0.05	0.05	0	0.00	0	0.01	0.00	0	0.01	0	0.01	0.01	0	0	0	0	0	0	0.02	0	0	0	0.07	0	0	0.04	0.01	0	0	0.47	0	0.03	0	0.00	0.05	0	0.01	0	0.02	0.00	0.03	0	1
RI	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0.09	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.88	0	0	0	0	0	0	0	0	0	0	0	1
SC	0	0	0	0.05	0.03	0	0	0	0	0.08	0.05	0	0	0	0.04	0	0	0.02	0.17	0	0	0	0	0	0.02	0.02	0	0.02	0	0	0	0.06	0	0	0	0.03	0	0	0	0	0.38	0	0.03	0.01	0	0	0	0	0	0	0	1
SD	0	0	0	0	0	0.02	0	0	0	0.16	0	0	0.07	0	0	0	0	0	0	0	0	0	0	0.06	0	0	0.01	0	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0.46	0	0.04	0	0.06	0	0	0.02	0	0.01	1
TN	0	0.02	0.03	0	0.13	0	0	0	0	0.11	0.06	0	0	0	0.02	0	0	0.01	0	0	0	0.01	0	0.00	0	0.01	0	0.10	0	0.01	0	0.01	0	0	0.01	0.04	0	0	0	0	0.00	0	0.38	0.02	0.00	0.03	0	0	0	0	0	1
TX	0	0.00	0.00	0.01	0.13	0.01	0	0	0	0.06	0.02	0.00	0	0	0.02	0	0	0.01	0.02	0.00	0.00	0	0.02	0.00	0.01	0	0	0.02	0	0.00	0	0.01	0.01	0.01	0.02	0.01	0.01	0	0.01	0	0.00	0	0.00	0.58	0	0.00	0	0.01	0	0	0	1
UT	0	0	0	0.02	0.28	0.03	0	0	0	0.03	0	0.00	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0.01	0.04	0.01	0	0.03	0.03	0	0	0.01	0	0.10	0.33	0.03	0	0.04	0.00	0	0	1
VA	0	0	0	0.00	0.08	0.05	0	0.01	0	0.05	0.03	0	0	0	0.01	0	0	0.01	0	0.02	0.08	0	0.00	0.01	0	0	0	0.05	0	0	0	0.01	0	0	0.02	0.02	0	0	0.11	0	0	0	0.00	0.05	0	0.38	0	0.01	0	0.01	0	1
VT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0.16	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0.74	0	0	0	0	1
WA	0	0	0	0.00	0.13	0.05	0	0	0	0.03	0	0	0	0	0	0	0	0	0	0.01	0.01	0	0	0.01	0	0.01	0	0	0	0	0	0.01	0	0.00	0.02	0.00	0	0.12	0	0	0	0	0	0.09	0	0	0	0.49	0.01	0	0	1
WI	0	0	0	0.01	0.02	0.01	0	0	0	0.04	0	0	0.02	0	0.11	0.00	0	0	0	0	0	0	0.08	0.14	0.03	0	0	0.01	0.01	0	0	0.00	0	0	0.00	0.02	0	0	0	0	0	0	0	0.01	0	0	0	0	0.48	0	0	1
WV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13	0	0	0	0	0	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	0.15	0	0	0.27	0	0	0	0	0	0	0.05	0	0	0	0.32	0	1

For a chain whose home state is AL, for example, its macroeconomic variable is the weighted sum of the macroeconomic variable in the 51 states where the weights are given by the first row.
Weights larger than or equal to 0.10 are highlighted.

A Proofs for Section 3.1

In this section, we show that, when ρ is small, $\frac{\partial^2 U}{\partial a \partial C} > 0$ at the interior solution to the franchisee's utility maximization problem. The first-order condition for the franchisee's expected utility maximization problem is

$$\begin{aligned}\frac{\partial U}{\partial a} &= \rho \int_{-\infty}^{\theta^*} - \Psi'(a)\, e^{-\rho[-\Psi(a)-L]} dF(\theta) \\ &+ \rho \int_{\theta^*}^{\infty} \left[(1-s) \frac{\partial G(\theta,a)}{\partial a} - \Psi'(a) \right] e^{-\rho[C+(1-s)G(\theta,a)-R(C,I)-\Psi(a)-L]} dF(\theta) = 0.\end{aligned} \tag{A.1}$$

The effect of increasing C on the marginal utility of effort at the interior solution is therefore

$$\begin{aligned}\frac{\partial^2 U}{\partial a \partial C} &= -\rho \Psi'(a)\, e^{-\rho[-\Psi(a)-L]} f(\theta^*) \frac{\partial \theta^*}{\partial C} \\ &+ \rho^2 \left(\frac{\partial R}{\partial C} - 1 \right) \int_{\theta^*}^{\infty} \left[(1-s) \frac{\partial G(\theta,a)}{\partial a} - \Psi'(a) \right] e^{-\rho[C+(1-s)G(\theta,a)-R(C,I)-\Psi(a)-L]} dF(\theta) \\ &- \rho \left[(1-s) \frac{\partial G(\theta^*,a)}{\partial a} - \Psi'(a) \right] e^{-\rho[C+(1-s)G(\theta^*,a)-R(C,I)-\Psi(a)-L]} f(\theta^*) \frac{\partial \theta^*}{\partial C}.\end{aligned} \tag{A.2}$$

Given that $R(C,I) - C = (1-s)\, G(\theta^*, a)$ according to equation (1) in the paper, the above expression can be simplified as follows:

$$\begin{aligned}\frac{\partial^2 U}{\partial a \partial C} &= -\rho (1-s) \frac{\partial G(\theta^*,a)}{\partial a} e^{-\rho[C+(1-s)G(\theta^*,a)-R(C,I)-\Psi(a)-L]} f(\theta^*) \frac{\partial \theta^*}{\partial C} \\ &+ \rho^2 \left(\frac{\partial R}{\partial C} - 1 \right) \int_{\theta^*}^{\infty} \left[(1-s) \frac{\partial G(\theta,a)}{\partial a} - \Psi'(a) \right] e^{-\rho[C+(1-s)G(\theta,a)-R(C,I)-\Psi(a)-L]} dF(\theta).\end{aligned} \tag{A.3}$$

The first term in (A.3) is positive because $\frac{\partial \theta^*}{\partial C} < 0$. In other words, with higher collateral, the repayment is smaller and it is less likely that the franchisee will default, and hence marginal effort yields greater returns. As a result, the franchisee has more incentives to work harder.

The second term captures the effect of wealth on incentives through affecting the marginal utility of wealth. This effect is negative.[29] The franchisee's wealth when she does not default is $C + (1-s)\, G(\theta,a) - R(C,I) - \Psi(a) - L$, which is increasing in C. Thus her marginal utility from additional wealth is decreasing in C. In other words, the marginal utility from working harder and generating more wealth when she does not default is decreasing in C. The magnitude of this negative effect of an increase in C on the franchisee's incentive to work is governed by ρ, which determines how marginal utility from wealth changes with the wealth level. Thus, when ρ is small, the positive effect of C on incentives (i.e., higher incentives due to a lower probability of defaulting, the first term in (A.3)) dominates the negative effect of C on incentives (i.e., lower incentives to increase payoff for a given probability of defaulting, the second term in (A.3)).

[29] Note that the second term in the first-order condition (A.1) is positive.

B Details on the Log-likelihood Function

In this section, we derive the log-likelihood function (18). It consists of three components: the likelihood that chain i starts franchising in year F_i, $p_i\left(F_i|\boldsymbol{u}_i\right)$; the likelihood that this chain is in the sample $p_i\left(F_i \leq 2006|\boldsymbol{u}_i\right)$; and the likelihood of observing its two growth paths, for the number of company-owned and the number of franchised outlets, $p_i\left(n_{cit}, n_{fit}; t = F_i, ..., 2006|F_i; \boldsymbol{u}_i\right)$.

First, the likelihood of observing F_i conditional on chain i's unobservable component of the arrival rate and its unobservable profitability of opening a franchised outlet is

$$p_i\left(F_i|\boldsymbol{u}_i\right) = \sum_{t'=B_i}^{F_i}\left[\prod_{t=B_i}^{t'-1}\left(1-q_t\right)\cdot q_{t'}\cdot\prod_{t=t'}^{F_i-1}\left(1-g\left(\boldsymbol{x}_{it};\boldsymbol{u}_i\right)\right)\cdot g\left(\boldsymbol{x}_{iF_i};\boldsymbol{u}_i\right)\right] \tag{B.4}$$

where t' represents when the chain starts to think about franchising, q_t is the probability that the chain is thinking about franchising in a specific year, and $g(\cdot,\cdot)$ is the probability of entry into franchising conditional on the chain thinking about it, given in equation (13). As explained above, $q_t = q_0$ in the year when the chain starts in business, denoted by B_i, (i.e., when $t = B_i$), and $q_t = q_1$ when $t > B_i$. Thus, the first summand in (B.4) (when $t' = B_i$) is $q_0\cdot\prod_{t=B_i}^{F_i-1}\left(1-g\left(\boldsymbol{x}_{it};\boldsymbol{u}_i\right)\right)\cdot g\left(\boldsymbol{x}_{iF_i};\boldsymbol{u}_i\right)$. It captures the probability that chain i is thinking of franchising from the very beginning, but chooses not to start franchising until year F_i. Similarly, the second summand in (B.4) (when $t' = B_i+1$) is $(1-q_0)q_1\cdot\prod_{t=B_i+1}^{F_i-1}\left(1-g\left(\boldsymbol{x}_{it};\boldsymbol{u}_i\right)\right)\cdot g\left(\boldsymbol{x}_{iF_i};\boldsymbol{u}_i\right)$, which captures the probability that chain i starts to think of franchising one year after it starts its business, but does not start franchising until year F_i. The sum of all such terms gives us the probability of starting franchising in year F_i.

Second, the likelihood of observing chain i in the sample, which requires that $F_i \leq 2006$, is the sum of the probability that chain i starts franchising right away ($F_i = B_i$), the probability that it starts one year later ($F_i = B_i + 1$), ..., and the probability that it starts in 2006, i.e.,

$$p_i\left(F_i \leq 2006|\boldsymbol{u}_i\right) = \sum_{F=B_i}^{2006} p_i\left(F|\boldsymbol{u}_i\right). \tag{B.5}$$

Third, to derive the likelihood of observing the two growth paths $(n_{cit}, n_{fit}; t = F_i, ..., 2006)$ of chain i conditional on its timing of franchising, note that the number of company-owned outlets in year t is given by equation (16), copied below:

$$n_{cit} = n_{cit-1} - \text{exits}_{cit-1} + \left(\text{new outlets}\right)_{cit}, \tag{B.6}$$

where $(n_{cit-1} - \text{exits}_{cit-1})$ follows a binomial distribution parameterized by n_{cit-1} and $1-\gamma$, the outlet exit rate; and $\left(\text{new outlets}\right)_{cit}$ follows a Poisson distribution with mean $m_i p_{ac}\left(\boldsymbol{x}_{it}, \boldsymbol{u}_i\right)$ or

$m_i p_{bc}(\boldsymbol{x}_{it}, \boldsymbol{u}_i)$ depending on whether the chain starts franchising before year t or not. Given that the mixture of a Poisson distribution and a binomial distribution is a Poisson distribution[30] and the sum of two independent Poisson random variables follows a Poisson distribution, n_{cit} follows a Poisson distribution with mean $\sum_{k=B_i}^{t} m_i p_c(\boldsymbol{x}_{ik}, \boldsymbol{u}_i)(1-\gamma)^{t-k}$, where $p_c(\boldsymbol{x}_{ik}, \boldsymbol{u}_i) = p_{bc}(\boldsymbol{x}_{ik}, \boldsymbol{u}_i)$ for $k < F_i$ and $p_c(\boldsymbol{x}_{ik}, \boldsymbol{u}_i) = p_{ac}(\boldsymbol{x}_{ik}, \boldsymbol{u}_i)$ for $k \geq F_i$. The likelihood of observing n_{cit} in the year the chain starts franchising (i.e., in the first year that we can observe this chain in the data) conditional on it starting franchising in year F_i is therefore

$$p_{n_{cit}|F_i}(\boldsymbol{u}_i) = \Pr\left(n_{cit}; \sum_{k=B_i}^{t} m_i p_c(\boldsymbol{x}_{ik}, \boldsymbol{u}_i)(1-\gamma)^{t-k}\right) \text{ for } t = F_i, \tag{B.7}$$

where $\Pr(\cdot; M)$ denotes the Poisson distribution function with mean M.

For subsequent years ($t = F_i + 1, ..., 2006$), we need to compute the likelihood of observing n_{cit} conditional on F_i as well as n_{cit-1}. According to equation (B.6), this conditional probability is the convolution of a binomial distribution ("$n_{cit-1}-\text{exits}_{cit-1}$" follows a binomial distribution with parameters n_{cit-1} and $1-\gamma$) and a Poisson distribution ($(\text{new outlets})_{cit}$ follows a Poisson distribution with mean $m_i p_{ac}(\boldsymbol{x}_{it}, \boldsymbol{u}_i)$):

$$\begin{aligned} & p_{n_{cit}|n_{cit-1},F_i}(\boldsymbol{u}_i) \\ & = \sum_{K=0}^{n_{cit-1}} \Pr(K|n_{cit-1}; 1-\gamma) \Pr\left((\text{new outlets})_{cit} = n_{cit} - K; m_i p_{ac}(\boldsymbol{x}_{it}, \boldsymbol{u}_i)\right), \end{aligned} \tag{B.8}$$

where K represents the number of outlets (out of the n_{cit-1} outlets) that do not exit in year $t-1$.

The conditional probabilities $p_{n_{fit}|F_i}(\boldsymbol{u}_i)$ and $P_{n_{fit}|n_{fit-1},F_i}(\boldsymbol{u}_i)$ can be computed analogously. Since Poisson events that result in company-owned and franchised outlet expansions are independent events, the likelihood of observing chain i's growth path $p_i(n_{cit}, n_{fit}; t = F_i, ..., 2006|F_i; \boldsymbol{u}_i)$ is the product of

$$\begin{aligned} & p_{n_{cit}|F_i}(\boldsymbol{u}_i), \text{ for } t = F_i; \\ & p_{n_{cit}|n_{cit-1},F_i}(\boldsymbol{u}_i), \text{ for } t = F_i + 1, ..., 2006; \\ & p_{n_{fit}|F_i}(\boldsymbol{u}_i), \text{ for } t = F_i; \\ & p_{n_{fit}|n_{fit-1},F_i}(\boldsymbol{u}_i), \text{ for } t = F_i + 1, ..., 2006. \end{aligned} \tag{B.9}$$

In our likelihood function, we also handle missing data. For example, data in 1999 and 2002 were not collected. When n_{cit-1} is not observable but n_{cit-2} is, we need to compute $p_{n_{cit}|n_{cit-2},F_i}$. Note that $n_{cit} = n_{cit-2} - \text{exits}_{cit-2} + (\text{new outlets})_{cit-1} - \text{exits}_{cit-1} + (\text{new outlets})_{cit}$, which can be

[30] If X follows a binomial distribution with parameters (M, p) and M itself follows a Poisson distribution with mean $\bar{M}$, then X follows a Poisson distribution with mean $\bar{M}p$.

rewritten as

$$\begin{aligned}&\text{outlets in } n_{cit-2} \text{ that do not exit before } t\\&+\text{new outlets in } t-1 \text{ that do not exit before } t\\&+\text{new outlets in } t,\end{aligned}$$

where "outlets in n_{cit-2} that do not exit before t" follows a binomial distribution with parameters $\left(n_{cit-2}, (1-\gamma)^2\right)$, "new outlets in $t-1$ that do not exit before t" follows a Poisson distribution with mean $m_i p_{ac}\left(\boldsymbol{x}_{it-1}, \boldsymbol{u}_i\right)(1-\gamma)$ and "new outlets in t" follows a Poisson distribution with mean $m_i p_{ac}\left(\boldsymbol{x}_{it}, \boldsymbol{u}_i\right)$. Therefore,

$$\begin{aligned}&p_{n_{cit}|n_{cit-2},F_i}\left(\boldsymbol{u}_i\right)\\=&\sum_{K=0}^{n_{cit-2}} \Pr\left(K|n_{cit-2};(1-\gamma)^2\right)\Pr\left((\text{new outlets})_{cit}=\right.\\&\left.n_{cit}-K; m_i p_{ac}\left(\boldsymbol{x}_{it-1},\boldsymbol{u}_i\right)(1-\gamma)+m_i p_{ac}\left(\boldsymbol{x}_{it},\boldsymbol{u}_i\right)\right).\end{aligned} \tag{B.10}$$

When more than one year of data is missing, we compute the corresponding conditional probability analogously. We then replace $p_{n_{cit}|n_{cit-1},F_i}$ and $p_{n_{fit}|n_{fit-1},F_i}$ in (B.9) by $p_{n_{cit}|n_{cit-2},F_i}$ and $p_{n_{fit}|n_{fit-2},F_i}$ when the observation of a year is missing, by $p_{n_{cit}|n_{cit-3},F_i}$ and $p_{n_{fit}|n_{fit-3},F_i}$ when data for two years are missing, and so on and so forth.

C Simulated Distributions of the Number of Outlets when Selection is Ignored

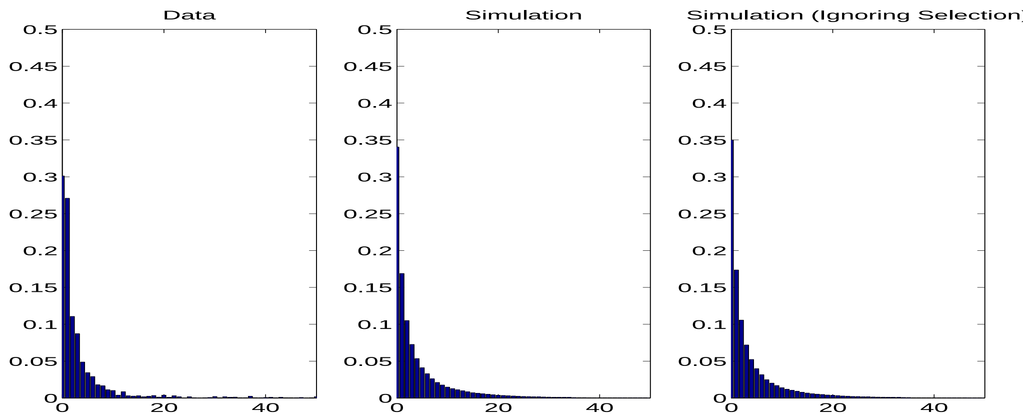
In this section, we show simulated distributions of the number of company-owned and franchised outlets when the decision on the timing of entry into franchising is ignored. Specifically, in these simulations we take the observed waiting time in the data as exogenously given. The simulated distributions are shown in the right panels of Figures C.1(a) and C.1(b). We also include the two panels in Figures 5(b) and Figure 5(c), which show the distribution in the data and the simulated distribution taking selection into account, respectively, as the left and the middle panels in Figure C.1(a) and Figure C.1(b), for comparison.

When we compare the middle panel of Figure C.1(a) (the simulated distribution of the number of company-owned outlets when selection is considered) and the right panel of the same figure (the simulated distribution when the timing of entry is ignored), we can see that these two distributions are very similar. This is because two effects are at play, and they apparently cancel each other out. On the one hand, chains that enter into franchising quickly tend to grow faster overall either because they are presented with more opportunities to open outlets or because outlets of these chains are more likely to be profitable. This effect was illustrated in Figure 1(a) in the paper. On the other hand, chains that enter fast into franchising are chains for which a franchised outlet is likely to be particularly profitable relative to a company-owned outlet. This effect was suggested by Figure 1(b). The latter effect shifts the distribution of the number of company-owned outlets to the left, while the first effect shifts the same distribution to the right.

The second effect is also consistent with the comparison of the middle panel and the right panel of Figure C.1(b) for the number of franchised outlets. The simulated distribution of the number of franchised outlets when the entry decision is taken as exogenous (in the right panel) is shifted to the left from the simulated distribution where the entry decision is endogenized (in the middle panel). In particular, the percentage of observations with zero franchised outlets is over predicted by 12%. This is because when we simulate the distribution in the right panel, we draw the unobservable profitability of a franchised outlet from the unconditional distribution. So even if the draw is not in favor of a chain opening a franchised outlet when an opportunity arrives, the simulated number of franchised outlets corresponding to this draw, which is most likely to be very small, is included to compute the distribution. When the timing of entry is endogenized, however, a chain with unfavorable draws is likely to delay its entry into franchising, and therefore may not be included in the computation of the conditional distribution of the number of franchised outlets.

Figure C.1: Simulated Distributions of the Number of Outlets when Selection is Ignored

(a) Number of Company-owned Outlets



(b) Number of Franchised Outlets