Customer Capital*

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Abstract

Firms spend substantial resources on creating and maintaining customer relationships. We explore the role of this customer capital for firm level and aggregate dynamics. Building on the neoclassical adjustment cost model of investment, we propose a tractable search theoretic general equilibrium model of long-term customer relationships. Frictional product markets require firms to spend resources on sales efforts, and cause existing customers to be partially locked-in. Our model implies that in more frictional product markets, where firms selling expenses are higher, measured profit rates, Tobin's Q and markups are higher. Sales and investment are less volatile and exhibit hump-shaped responses to shocks. As a result, the model also reproduces the well-documented failure of investment-Q regressions. We document that these patterns are present in Compustat data.

Firms spend substantial resources on marketing and selling their products.[1] While concerns of building and maintaining customer base are commonplace in both the marketing and industrial organization literatures, they have been challenging to incorporate into the general equilibrium models used by macroeconomists. This paper develops a tractable search theoretic general equilibrium model that allows analysing the effects of customer base concerns both on the firm and the aggregate level. We then proceed to study its implications in Compustat data.

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[1]US businesses spend almost $300 billion a year on advertising alone.

To model long-term customer relationships we assume consumers face informational frictions regarding product characteristics. Our model features a cross-section of firms, which use capital and labor to produce differentiated goods, which are then sold to a representative household through a frictional market. Product differentiation is such that not all members of the household want to purchase all goods, and the only way a potential customer can determine whether he is willing to buy a particular firm's product is to inspect it in person. To allow this inspection to take place, firms must spend resources on marketing and sales efforts i.e. hire sales people. Sales people have limited capacity in the number of customers they can serve, however, which limits the ability of a firm to expand quickly. On the other hand, because product search is time-consuming, existing customers continue to buy from the same firm for some time. Firms control their customer acquisition both through the size of their sales force and their pricing. We assume that pricing in these long-term customer relationships reflects the inability of firms to commit to maintaining low prices for customers who are locked in, but allows firms to commit to offering initial discounts to attract new customers.[2]

The model has a number of implications. First, the frictional product markets generate a form of intangible capital embodied in the firm's customer base. When customer relationships are long term in nature and the costs of acquiring customers paid up front, the present discounted value of future profits from the customer relationship must make up for these costs, implying that existing customers are valuable assets to the firm. It follows that even though the model is fully competitive, markups are positive, profit rates exceed the cost of capital, and firm value exceeds the value of the stock of capital. The model thus captures one form of the intangible capital contributing to the wealth of economies, while largely remaining outside formal accounts. Recent research has emphasized the role of intangible capital for explaining various macroeconomic phenomena, calling for more formal work investigating its effects (e.g. Hall 2001, Atkeson and Kehoe 2005, McGrattan and Prescott 2010a, McGrattan

[2]Concrete examples of products motivating our model are newspapers subscriptions and cell phone services. Newspapers offer discounts to new customers, subsequently charging a price above the marginal cost of production for an extended period of time. Similarly, cell phone providers often offer an initial discount in the form of a free phone. In these industries it appears common to evaluate the value of a firm based on the number of customers, the retention rate, and the margin per customer. We believe that the main insights of our analysis are more general, however, applying also to markets where contracts are implicit.

and Prescott 2010b, Eisfeldt and Papanikolaou 2009).

Second, the frictional product markets affect firm dynamics in response to both aggregate and firm level shocks. On the one hand, by imposing an additional adjustment cost on firms, these frictions reduce the variability of firm sales, profits, Tobin's Q, as well as investment. On the other, they change the timing of firm responses. While in the neoclassical adjustment cost model of investment firms respond to a positive productivity shock with an on-impact increase in investment, when product markets are frictional firms need to first build up their customer base by increasing sales efforts. When customer base expansion involves convex costs, it acts as a bottleneck holding firms back from investing in physical production capacity until their customer base has grown sufficiently. Product market frictions thus lead to hump-shaped responses not only in sales, but also investment. While hump-shaped responses are a pervasive finding in empirical macroeconomics (Cogley and Nason 1995), the neoclassical benchmark model does not generate them. In particular, recent literature has emphasized the slow adjustment of investment to shocks (Christiano, Eichenbaum, and Evans 2005), reverting to special adjustment cost functions to generate these patterns. The above dynamics suggest that customer base concerns may provide a natural micro-foundation for these investment responses.

Third, these changes in dynamics suggest potentially interesting predictions for the investment-Q regressions studied in the empirical finance literature. This literature documents that the simple prediction of the neoclassical adjustment cost model of investment – that Tobin's Q is a sufficient statistic for firm investment – has little success empirically (for a survey, see Caballero 1999). Instead, firm cash flow appears more useful for explaining investment. The model offers a potential explanation for these observations by breaking the perfect correlation between investment and Tobin's Q implied by the neoclassical model, as well as introducing a natural link between the responses of investment and profit rates to shocks. In the model investment exhibits a hump-shaped response to shocks, which need not be shared by Tobin's Q. Firm profits, on the other hand, typically share the hump-shaped response, both because the costs of expanding the customer base are expensed from profits, and because profits grow with the customer base.

After illustrating these effects in the model, we turn to Compustat data for evidence. We sort industries based on the degree of spending on customer acquisition – a proxy for the degree of friction in these markets – and document support for the above patterns in the data.

The paper is organized as follows. Section 1 discusses related literature. Section 2 presents our model and Section 3 studies its implications. Section 4 discusses the empirical evidence.

1 Related Literature

The notion of a customer market, first formalized by Phelps and Winter (1970), has a long tradition in macroeconomics – albeit one which has suffered from difficulties in modeling, which have diverted researchers to the tractable monopolistic competition framework of Dixit and Stiglitz (1977) instead. Important contributions include Bils (1989) and Rotemberg and Woodford (1991), seeking to understand the cyclical behavior of markups. The literature remains active, with recent contributions e.g. by Ravn, Schmitt-Grohe, and Uribe (2008), Nakamura and Steinsson (2008) and Kleshchelski and Vincent (2009). These papers typically focus on firm price-setting behavior and markups: the first under consumption habits, the second under asymmetric information, and the third in a dynamic general equilibrium model with market share concerns. Our focus is on the effects on quantities instead, which may provide more direct evidence on the impact of customer base concerns.[3]

The notion of a customer base is commonplace in the marketing and industrial organization literatures. Within industrial organization, the customer base is often associated with switching costs rather than search frictions, however (for surveys, see e.g. Klemperer 1995, Farrell and Klemperer 2007). The firm dynamics we emphasize stem from convex costs to customer base expansion, so potentially they could arise from switching costs as well, if such convexities were present. Recent empirical work within industrial organization documents that firm expansion appears constrained by customer base concerns: Foster, Haltiwanger,

[3]The only paper we are aware of in this literature which considers the interactions of physical investment and the customer base is Lundin, Gottfries, Bucht, and Lindstrom (2009), who show that financial constraints may lead to sluggish price adjustment in a customer market.

and Syverson (2009) show that, in US manufacturing, new plants face a demand gap relative to existing plants which closes only slowly as plants mature. In a related vein, customer base concerns are becoming increasingly recognized also within the international trade and international macroeconomics literatures, where recent research uses them to explain exports and international pricing (Alessandria 2004, Arkolakis 2008, Drozd and Nosal 2008, Eaton, Eslava, Kugler, Krizan, and Tybout 2010).

2 The Model

The model economy is populated by a representative household and a cross section of firms. In this section we consider an environment where firms experience idiosyncratic shocks causing them to expand and contract over time, but where there is no aggregate level variation and the distribution of firms remains stationary. The model is straightforward to extend also to a setting where the idiosyncratic shocks are replaced by aggregate shocks, however, a case we return to later.

2.1 Goods

There are two types of goods in the economy: a continuum of differentiated goods and one homogenous good. Each firm produces a differentiated good, which is sold to the household through a frictional market. Once the household receives the differentiated good, it converts it one-for-one into the homogenous good, which can be used for consumption and investment. This homogenous good acts both as the medium of exchange and the numeraire in the economy, but each unit of the good must be procured through the frictional product market.

2.2 Firms

Production is carried out by a continuum of firms with Cobb-Douglas production technologies $y = f(k, l, z)$. Capital k accumulates with the law of motion $k_{t+1} = (1-\delta_k)k_t + i_t$, where δ_k is the depreciation rate of capital, and investment i entails a physical adjustment cost $\phi(i, k)$.

Firms hire labor l at a frictionless market with wage w. Firm-specific productivity z follows a Markovian stochastic process with a bounded support and a continuous and monotone transition function P.

Each firm produces a differentiated good, but not all potential customers are willing to buy all goods. We assume that product differentiation is done in such a way that a potential customer can only determine whether he is willing to buy a firm's product by meeting with a firm representative to inspect the good in person. To allow these meetings to take place, firms must hire sales people. The measure of effective sales people s is associated with an increasing and convex cost $\kappa(s)$ – as the desired measure of effective sales people increases, the firm must expand to less profitable locations and less successful sales people.

Product inspection is affected by congestion because sales people are placed in different locations, and have finite capacity for meetings with potential customers. If the total measure of potential customers arriving to inspect the firm's product during a period is b, the measure of new customer relationships is $M(b,s) = \xi b^{\gamma} s^{1-\gamma}$, where $\xi > 0$ and $\gamma \in (0,1)$. This measure is a product of the number of meetings taking place and the probability that a potential customer is willing to buy the firm's good. The measure of meetings increases in potential customers arriving, but at a diminishing rate if sales people are fixed, as a share of additional customers are bound to end up in locations where sales people are busy with other customers. The measure also increases in sales people, but at a diminishing rate if the number of potential customers is fixed, as additional sales people cannot be perfectly coordinated to the exact sales locations with an excess of arriving customers at each instant.[4] Using $\theta = \frac{b}{s}$ to denote potential customers per sales person, the rate matches form per sales person is $\eta(\theta) = \xi\theta^{\gamma}$.

The frictions in creating new customer relationships make these relationships long-term in

[4]Stevens (2007) describes a such a "telephone line" matching process, which results in an approximately Cobb-Douglas matching function. The underlying idea is a queueing process where sales people are placed in separate locations and handle customers at a finite rate. Customers contact sales people at a finite rate, but cannot coordinate on which sales people they contact. Upon contacting a sales person, a potential customer may thus find them busy with another customer. Increasing the number of customers implies that sales people spend less time idle, increasing the number of matches, but at a diminishing rate because idle time is limited. On the other hand, increasing sales people increases the odds that a customer will find a sales person idle, increasing the number of matches, but at a diminishing rate because customers cannot coordinate on which sales person they contact.

nature. How are prices determined in these relationships? We allow firms to influence the measure of new customer relationships through pricing, as well as to differentiate between new and existing customers. First, existing customers purchase one unit of the good until the relationship ends, either due to attrition at rate δ_n or endogenously because the value of the relationship becomes negative. The customer values one unit of the differentiated good as one unit of the homogenous good, so the highest price the firm can charge for it is one unit of the homogenous good. We assume the firm cannot commit to promising a lower price for these customers. Second, we assume the firm can commit to an initial discount for new customers. Firms (rationally) anticipate that the measure of potential customers per sales person is an increasing and convex function $\Theta(\varepsilon)$ of the discount ε, where Θ is an equilibrium object.

The firm's Bellman equation reads

$$v(k,n,z;w,\Theta) = \max_{\varepsilon,i,l,s,y} y - wl - w\kappa(s) - \phi(i,k) - s\eta(\Theta(\varepsilon))\varepsilon + \beta \int v(k',n',z';w,\Theta)P(z,dz')$$

$$y \leq n + s\eta(\Theta(\varepsilon)), \tag{1}$$

$$y = f(k,l,z), \tag{2}$$

$$k' = (1-\delta_k)k + i, \tag{3}$$

$$n' = (1-\delta_n)y. \tag{4}$$

The firm sells the produced differentiated good y to its customers at price one i.e. the price of the homogenous good. Using the sales revenue, the firm then pays the wages of production and sales personnel, the costs of physical investment, as well as giving the discounts promised to new customers. Because the firm's sales are constrained by the size of its customer base, equation (1) states that production output is no greater than the customer base, where n is the existing customer base and $s\eta(\Theta(\varepsilon))$ the measure of new customers for a firm with sales personnel s and discount ε. Equation (2) determines the labor needed to produce the desired output given productivity and existing capital $\ell(k,y,z)$. Finally, equation (3) is the law of motion for capital, and equation (4) the law of motion for the customer base, where δ_n is the depreciation rate of customers, capturing attrition due to idiosyncratic reasons.

Due to constant returns to scale in production, if product and capital markets were frictionless, all production would be taken over by the highest productivity firm. When the product market is frictional, however, decreasing returns in customer acquisition allow also less productive firms to continue producing and selling their goods. In normal times each firm will thus choose some positive level of sales personnel to maintain their customer base, which otherwise shrinks due to attrition. A firm that faces a particularly bad productivity realization however, might also choose to contract its customer base by more than it naturally depreciates. How likely this event is depends on the depreciation rate, the size and persistence of the shock, as well as the adjustment cost to capital. Because we view both the depreciation rate of the customer base as well as the physical adjustment costs as relatively large, it is useful to simplify notation by assuming such contractions will not be optimal in equilibrium.

Customer Acquisition Using the Bellman equation, the marginal value of an additional customer can be written as

$$v_n(k, n, z; w, \Theta) = 1 - w\ell_y(k, y, z) + \beta(1 - \delta_n) \int v_n(k', n', z'; w, \Theta) P(z, dz'). \tag{5}$$

An additional customer increases today's sales revenue by one unit, and today's production costs by the marginal cost $w\ell_y(k, y, z)$. With probability $1 - \delta_n$ the customer remains with the firm also the following period, delivering the discounted value $\beta E_z v_n(k', n', z'; w, \Theta)$.

The optimal measure of sales people equates the marginal cost of acquiring a new customer to the marginal value of an additional customer

$$w\frac{\kappa'(s)}{\eta(\theta)} + \varepsilon = v_n(k, n, z; w, \Theta), \tag{6}$$

where $\theta = \Theta(\varepsilon)$. Here the marginal cost, on the left, consists of both the wages of additional sales people as well as the discount given to new customers. These up-front costs of acquiring new customers imply that existing customers are valuable to firms.

The optimal discount is characterized by

$$1 = \frac{\eta'(\theta)\Theta'(\varepsilon)}{\eta(\theta)}[v_n(k, n, z; w, \Theta) - \varepsilon]. \tag{7}$$

The left hand side represents the marginal cost of increasing the discount, the decrease in sales revenue per new customer, and the right the corresponding increase in firm value, as the inflow of new customers per sales person increases by $\frac{\eta'(\theta)\Theta'(\varepsilon)}{\eta(\theta)}$, with each new customer increasing firm value by $v_n(k, n, z; w, \Theta)$. The size of the optimal discount depends on how severe is the congestion in matching, captured by the elasticity of the matching function. If sales people cannot accommodate additional customers per period, there is no point in increasing discounts to attract more customers.[5]

Physical Investment The first-order condition for investment is familiar,

$$\phi_i(i, k) = \beta \int v_k(k', n', z'; w, \Theta) P(z, dz'), \tag{8}$$

relating the marginal cost of investing today to the value of additional capital next period, also known as marginal Q. Adopting the common quadratic adjustment cost function implies a linear relationship between the investment rate $\frac{i}{k}$ and marginal Q. If the product market is frictionless, it then follows that the investment rate should be a linear function also of Tobin's Q, $v(k', n', z'; w)/k'$, as the latter equals marginal Q.[6] Frictional product markets break this linear relationship by introducing a time-varying wedge between marginal and Tobin's Q, useful for understanding the weak correlation of the two variables in the data.

2.3 Representative Household

The representative household consumes the homogenous good and leisure, with preferences

$$\sum_{t=0}^{\infty} \beta^t u(c_t, 1 - l_t^m - l_t^s). \tag{9}$$

[5]Section 2.3 shows that in equilibrium $\Theta(\varepsilon) = (\frac{\xi\varepsilon}{w})^{\frac{1}{1-\gamma}}$.
[6]See Hayashi (1982).

The household is endowed with one unit of time per period, dividing it between market work l_t^m, product search l_t^s, and leisure. The household's income consist of dividend and labor income, both paid in the homogenous consumption good. Normalizing the price of the homogenous good to one, the household's per-period budget reads

$$c_t \leq w(l_t^m + l_t^s) + D, \quad \forall t \geq 0. \tag{10}$$

The household owns all the firms in the economy, receiving the aggregated dividends D. As explained in the next section, market work and product search pay the same return w in equilibrium. Both the aggregated dividends and the wage are constant in a stationary equilibrium.

Product Search Each infinitesimal household member allocated to product search does so independently, without household coordination, seeking to maximize the return to search. Maintaining existing customer relationships does not require effort on their part, allowing them to continually seek new relationships. For thinking about the returns to search, it is useful to start with the return to existing relationships, however. A customer relationship continues for as long as the household member is willing to continue to buy one unit of the good per period, unless it is severed by an exogenous separation shock. Because the household member values the differentiated good at one unit of the homogenous good, the household is happy to pay up to one unit per period. Maximizing profits, the firm sets the price to one unit. In principle the firm could schedule these payments in different ways over time, maintaining the same present value, but if the firm cannot commit to future prices, then it will price at one unit each period. Assuming the firm cannot commit in the long run thus implies that the return to existing customer relationships is zero. We allow the firm to commit to an initial discount, however, to attract potential customers to inspect the firm's product.

Each searching household member chooses which firm to contact, aware of the discounts offered by all firms, and anticipating that firms offering larger discounts attract more potential customers per sales person, increasing the expected waiting time to meet with a sales

person. If a household member decides on a firm with discount ε and ratio of potential customers per sales person θ, the return to search for that household member is $\mu(\theta)\varepsilon$. New customer relationships are born at rate $\mu(\theta) = \xi\theta^{\gamma-1}$, and the firm then delivers one unit of the differentiated good to the household member each period for as long as the relationship lasts. Converting the good into the homogenous good, the household pays the firm $1-\varepsilon$ units in the first period and one unit in later periods. This leaves the household member with a return of ε units in the first period, and zero in later periods.

Finally, the return to search must be the same across all firms attracting customers, and equal to the opportunity cost of search i.e. working at wage w,

$$w = \mu(\theta)\varepsilon. \tag{11}$$

This equation implicitly defines an increasing relationship between the discount a firm offers and the measure of potential customers per sales person attracted by the discount. Solving the equation for θ yields the function: $\Theta(\varepsilon) = (\frac{\xi\varepsilon}{w})^{\frac{1}{1-\gamma}}$.

PROPOSITION 1. *Given a firm's sales personnel s, equations* (6)*,* (7) *and* (11) *determine a firm's discount and measure of potential customers per sales person as $\varepsilon = \frac{w}{\xi}[\kappa'(s)\frac{\gamma}{1-\gamma}]^{1-\gamma}$, and $\theta = \kappa'(s)\frac{\gamma}{1-\gamma}$. For a convex $\kappa(s)$ they imply that firms hiring more sales people also offer larger discounts and attract more potential customers per sales person.*

2.4 Aggregation

This section defines a distribution of firms as well as a number of aggregate variables that appear in the definition of equilibrium. We denote the cross-sectional distribution of firms across physical capital, customer capital and productivity by $\lambda(k, n, z)$. It evolves over time according to a law of motion $\lambda' = T(\lambda; w, \Theta)$, determined by the productivity process and firm decision-making, but our focus is on a stationary distribution. Integrating over this stationary distribution, total output per period is $Y(\lambda; w, \Theta) = \int y(k, n, z; w, \Theta)d\lambda(k, n, z)$, and total spending on investment $\Phi(\lambda; w, \Theta) = \int \phi(i(k, n, z; w, \Theta), k)d\lambda(k, n, z)$. The total demand for labor, adding up production and sales, is $L^d(\lambda; w, \Theta) = \int l(k, n, z; w, \Theta) +$

$\kappa(s(k,n,z;w,\Theta))d\lambda(k,n,z)$.

With this, we can write the aggregated dividends received by the household as

$$\begin{aligned} D(\lambda;w,\Theta) =& Y(\lambda;w,\Theta) - wL^d(\lambda;w,\Theta) - \Phi(\lambda;w,\Theta) \\ & - \int s(k,n,z;w,\Theta)\eta(\Theta(\varepsilon(k,n,z;w,\Theta)))\varepsilon(k,n,z;w,\Theta)d\lambda(k,n,z). \end{aligned}$$

2.5 Equilibrium

The definition of equilibrium embeds the notion of a competitive search equilibrium (Moen 1997) into a standard definition of a stationary equilibrium with a cross section of firms.[7]

DEFINITION 1. A stationary competitive search equilibrium specifies: i) household decision rules $L^m(w, D(w,\Theta))$, $L^s(w, D(w,\Theta))$, $C(w, D(w,\Theta))$, ii) firms' decision rules $\varepsilon(k,n,z;w,\Theta)$, $i(k,n,z;w,\Theta)$, $l(k,n,z;w,\Theta)$, $s(k,n,z;w,\Theta)$, $y(k,n,z;w,\Theta)$ and value function $v(k,n,z;w,\Theta)$, iii) aggregate quantities $Y(\lambda;w,\Theta)$, $\Phi(\lambda;w,\Theta)$, $L^d(\lambda;w,\Theta)$, $D(\lambda;w,\Theta)$, iv) wage w, v) function $\Theta(\varepsilon)$, and vi) distribution of firms λ, such that

1. The firms' decision rules and value function solve their Bellman equation.
2. The household's decision rules maximize (9) subject to (10), and optimal search behavior implies $\Theta(\varepsilon)$ satisfies (11).
3. Labor market clears: $L^m(w,\Theta) = L^d(\lambda;w,\Theta)$ and $L^s(w, D(w,\Theta)) = \int s(k,n,z;w,\Theta)\Theta(\varepsilon(k,n,z;w,\Theta))d\lambda(k,n,z)$.
4. Goods market clears: $C(\lambda;w,\Theta) + \Phi(\lambda;w,\Theta) = Y(\lambda;w,\Theta)$.
5. Consistency: The distribution of firms λ follows the law of motion $\lambda' = T(\lambda;w,\Theta)$, with $\lambda' = \lambda$.

[7] See e.g. Gomes (2001).

3 The Impact of Customer Capital

In this section we parameterize the model to illustrate the impact of customer base concerns on sales, selling expenses, investment, profits, and values. The first set of implications from the model involve level effects, and the second responses to shocks. It makes little difference for our main predictions whether these shocks are idiosyncratic or aggregate. For purposes of illustration we focus on idiosyncratic shocks here, commenting on the differences with aggregate shocks at the end of the section.

Parametrization We parameterize the model as described in Table 1. Many of the parameters are standard in the literature, and set according to convention. There is relatively little previous work with frictional product markets, and hence the parameters associated with these are not as well established, leading us to seek broadly reasonable values based on available evidence. For the depreciation rate of the customer base, we adopt the value used by Hall (2008), $\delta_n = 20\%$ per year. For parsimony, the convex cost of sales effort is assumed quadratic: $\kappa(s) = \kappa\frac{s^2}{2}$. We set the coefficient κ of the adjustment cost function, and the coefficient ξ and elasticity γ of the matching function to accommodate the following targets: First, the share of marketing expenditures in GDP is set to an average 4%. This is a moderate estimate, as advertising alone accounts for roughly 2% of GDP per year (see e.g. Hall (2008)), while our notion of sales effort is broader. Second, we set the average markup to 10%. This number is less than the values which are usually targeted (around 15 to 20%): we do so because our model is competitive and it is likely that in the data, some of the markups reflect market power. Finally, we set the amount of time spent by customers in product search to one hour per week. In principle time use surveys (such as the one carried out by the BLS) shed light on this, but it is difficult to separate time spent searching from time spent in the logistics of procuring consumption goods. These three targets pin down the three parameters κ, γ and ξ.

Levels The degree of friction in the product market, responsible for rendering the customer base a state variable, is governed by the matching function coefficient ξ. As ξ rises, the speed

Table 1: Parametrization

β	discount rate	.95
ρ_z	persistence of productivity	.8
σ_z	st.dev. of productivity	.1
α	share of capital	.3
δ_k	depreciation of capital	.1
η_k	elasticity of adj. cost	1
δ_n	depreciation of customers	.2
κ	sales cost parameter	107.4
γ	matching function parameter	0.14
ξ	matching function parameter	1.15

Notes: $\phi(i,k) = \frac{\eta_k}{2}(\frac{i}{k} - \delta_k)^2 k$.

of matching rises and the model approaches the neoclassical benchmark model. Along the way the labor allocated to both sales and product search diminishes, and customer capital loses its value. In the frictionless limit the firm's profit rate just makes up for the opportunity cost of capital, $r+\delta_k$, markups are zero, and firm value is determined by the value of physical capital, so Tobin's Q equals one. Figure 1 illustrates these level effects, with the frictionless limit on the left and frictions increasing toward the right. The baseline parametrization is marked by the vertical line, with an implied Tobin's Q of approximately 1.7. Firm value exceeds the value of physical capital due to the intangible capital embodied in the customer base of the firm: When the costs of acquiring customers are paid up front, the present discounted value of future profits from the customer relationship must make up for these costs, implying that existing customers are valuable assets to the firm. Firm profit rates and markups must therefore exceed those in the neoclassical benchmark model. One variable which remains unaffected is the investment rate $\frac{i}{k}$, however, which continues to just make up for the depreciation of physical capital at rate δ_k.

These changes in the market values of firms are interesting because they capture one form of the intangible capital which contributes to the wealth of economies, while largely remaining outside of formal accounts. One indication of this wealth is the empirical observation that the market value of firms generally well exceeds the value of physical capital (Hall 2001). Recent research has emphasized that intangible capital can play an important role in explaining



Figure 1: Impact of friction on steady-state

Notes: The figure plots the steady-state of the model varying the matching function parameter ξ. As ξ rises, the steady-state approaches that of the neoclassical model. The vertical line indicates the baseline parametrization described in the text.

various macroeconomic phenomena, calling for more formal work investigating its effects (e.g. Atkeson and Kehoe 2005, McGrattan and Prescott 2010a, McGrattan and Prescott 2010b, Eisfeldt and Papanikolaou 2009). While the general notion of intangible capital is quite broad, this paper seeks to contribute by analyzing one specific form of intangible capital more closely.

Dynamics By curbing sales growth, product market frictions effectively impose an additional adjustment cost on firms. A natural implication of this is a dampening in firms' responses to shocks. Figure 2 illustrates this dampening in the model, by studying how the impulse response to a positive TFP shock changes as frictions increase from the neoclassical benchmark to the baseline parametrization. The figure shows a reduction in volatility across the board: sales, investment, profit rates, and Tobin's Q.

The figure also reveals changes in the timing of responses to the shock, affecting in particular investment in physical versus customer capital. To understand these changes, consider first

the neoclassical benchmark model shown by the dashed line. In this case the increase in productivity causes the firm to expand its production capacity, with the physical adjustment cost to investment smoothing this expansion over a period of time. The shadow value of additional capital jumps up on impact, and the first order condition for investment (8) implies the same pattern for the investment rate I/K. Since the usual homogeneity assumptions are satisfied in our model, Tobin's Q equals the shadow value of capital, and therefore the response of Tobin's Q to the shock is identical to that of the investment rate.

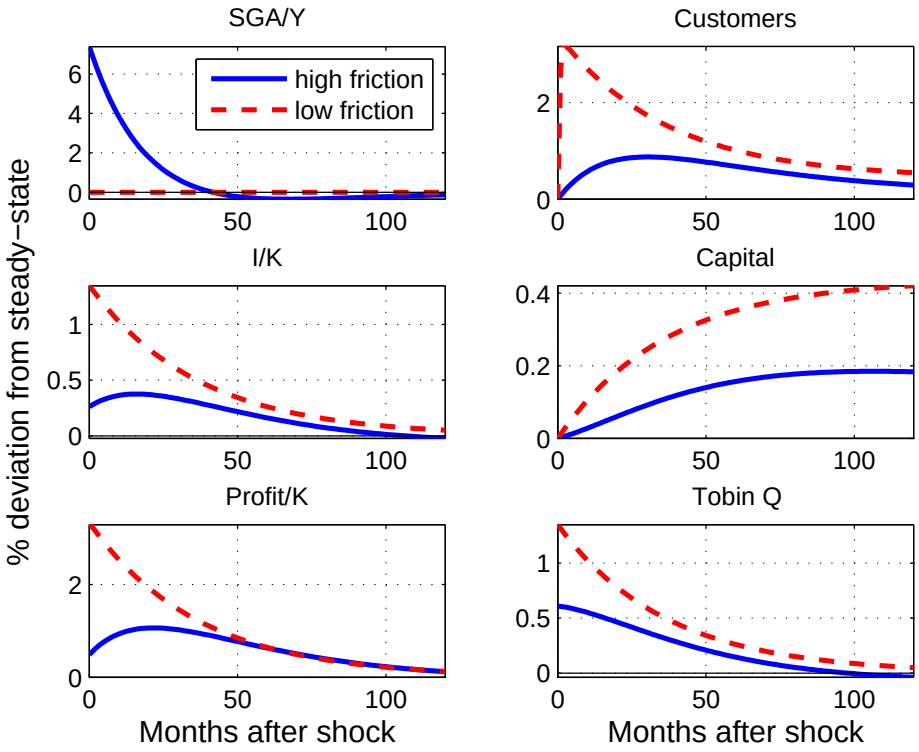


Figure 2: Responses to TFP-shock

Notes: The variables are in % deviations from steady-state.

In contrast, when product market frictions are non-negligible, not only is firm expansion constrained also by the costs of expanding the customer base, but these costs become particularly important in the short run. The solid line shows the firm response for the baseline parametrization. When productivity increases, production output increases even if inputs are held fixed, leaving the firm short of customers. The first order of business following the shock is therefore to increase sales efforts, and build up the customer base. As above, the

increase in productivity causes the firm to expand its production capacity over time, but investment in physical capital is now constrained also by the costs of expanding the customer base: Investment reaches its peak intensity only as the customer base expansion allows. Interestingly, in this case Tobin's Q no longer explains well the response of investment to the shock. Tobin's Q is a forward looking variable reflecting the value of the intangible capital embodied in the customer base (as well as future profits from future new customers). In response to the shock this customer capital appreciates, but there is no sign of a hump-shape in the response. The figure suggests that firm profits should in fact work better at explaining investment. Profits share the hump-shaped responses of investment for two reasons: i) the initial investment into customer capital is expensed from profits by standard accounting practices, and ii) profits grow as the customer base grows.

These hump-shaped responses are interesting because while hump-shaped responses are a pervasive finding in empirical macroeconomics (Cogley and Nason 1995), the neoclassical benchmark model does not generate them. In particular, recent literature has emphasized the slow adjustment of investment to shocks (Christiano, Eichenbaum, and Evans 2005), reverting to special adjustment cost functions to generate these patterns. The above dynamics suggest that customer base concerns may provide a natural micro-foundation for these investment responses.[8]

Investment Regressions The above dynamics suggest potentially interesting predictions for the investment-Q regressions studied in the empirical finance literature. This literature documents that the simple prediction of the neoclassical adjustment cost model of investment – that Tobin's Q should be a sufficient statistic for firm investment – has little success empirically. As the figure illustrates, the customer expansion friction breaks the direct link between investment and Tobin's Q, and offers an explanation for why profit rates may help explain investment. To study the implications of the model for investment regressions, we simulate a balanced panel of firms from the model and run the following Q-regressions, as

[8]Note that incorporating frictional labor markets (rather than product markets) would also impose an additional adjustment cost on firm expansion, dampening firm responses to shocks. Because the dynamics of investment described above rely on the complementarity of customer capital with physical capital, however, it is not clear that frictional labor markets could generate the same patterns, e.g. for investment.

well as Q-regressions augmented with cash flows, in this simulated data:

$$\frac{I_{it}}{K_{it}} = b_0 + b_1 Q_{it} + \varepsilon_{it}, \tag{12}$$

$$\frac{I_{it}}{K_{it}} = b_0 + b_1 Q_{it} + b_2 \frac{CF_{it}}{K_{it}} + \varepsilon_{it}, \tag{13}$$

where $Q_{it} = \beta E_t V_{it+1}/K_{it+1}$ is Tobin's Q, and CF_{it} the cash flow, measured as output net of labor costs and sales costs.[9]

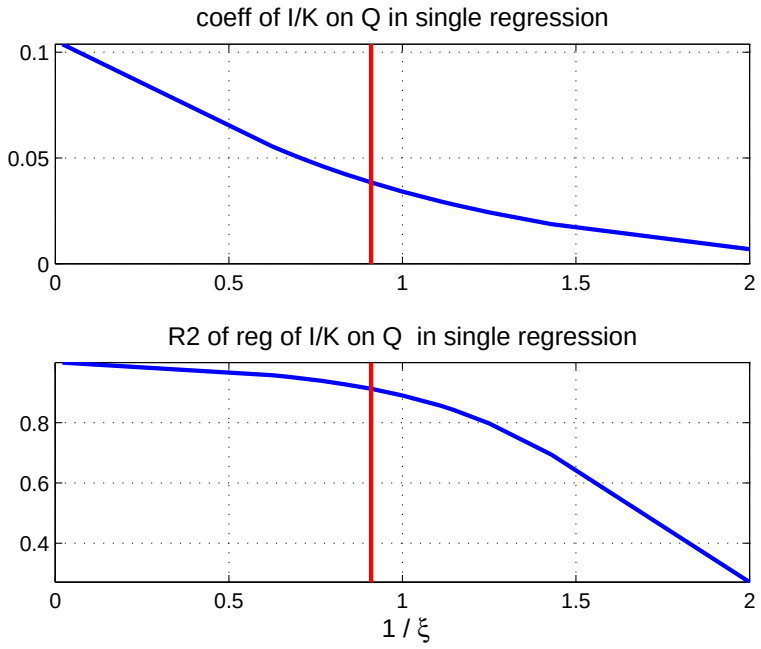


Figure 3: Impact of friction on Q-regression

Notes: This figure reports the coefficient on Q (b_1) as well as the R^2 from regression (12) on simulated data from the model. The vertical line indicates the baseline parametrization.

Figure 3 presents the coefficient estimates from regression (12), as a function of the degree of friction. In the frictionless limit, this Q-theory regression works perfectly: (i) the coefficient on Q equals the inverse of the adjustment cost coefficient, and (ii) the R^2 is 100 percent. As the friction increases, however, both the coefficient on Q and the R^2 fall. Figure 4 presents the coefficient estimates from the cash flow augmented regression (13). In the frictionless

[9] Without the cashflow term, this would be the exact regression specified by the Hayashi model. Note that the timing is driven by the one-period time-to-build, hence the time-t investment is related to the expected value next period.

limit cash flow does not matter, and investment is explained by Q just as the theory predicts. But as the frictions increase, not only do both the coefficient on Q and the R^2 fall, but cash flow becomes significant.

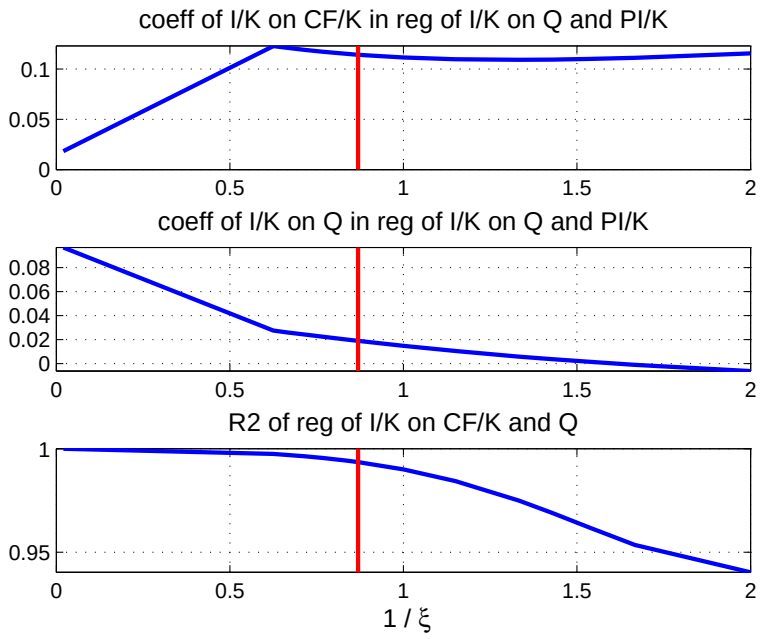


Figure 4: Impact of friction on Q-regression with cash flow

Notes: This figure reports the coefficients on Q (b_1) and cash flow (b_2) as well as the R^2 from regression (13) on simulated data from the model. The vertical line indicates the baseline parametrization.

These figures make two substantive points related to interpreting results from such regressions: First, note that the baseline parametrization implies a clearly lower coefficient on Q than the neoclassical benchmark model does. Inferring the magnitude of the physical adjustment cost from the regression coefficient on Q would thus lead to substantially overestimating these adjustment costs. Second, the observation that investment is more correlated with firm profits than Tobin's Q need not imply that firms are financially constrained, especially in markets where customer capital is important.

There are naturally a number of alternative theoretical reasons that could potentially explain why investment-Q regressions do not work well empirically. One possibility is the decreasing returns to scale technology which plays an important role in allowing Cooper and Ejarque (2003) to fit the empirical investment regression results. While their paper does not discuss

the details of the mechanism generating these results, that mechanism necessarily differs from ours because the dynamics of customer base accumulation play no role in their model. Other possibilities include financial constraints and non-smooth adjustment costs. However, as Caballero and Leahy (1996) and Gomes (2001) argue, even if models incorporating these features no longer imply a simple relation between investment, marginal Q and average Q, numerical simulations of those models typically reveal a strong relation between investment and Tobin's Q, reinforcing the puzzle of the failure of Q-theory in the data.[10] Our model does imply a testable implication that can be used to distinguish it from alternative theories: In industries where customer base concerns are more important, these regressions should work less well. We study this prediction in the next section.

Although we have focused on firm level shocks above, the main predictions regarding volatility and hump-shaped responses in investment continue to hold also in response to aggregate shocks. The main difference with aggregate shocks would seem to be that the predictions regarding the investment-Q regressions become less clear, because the responses of profits and Tobin's Q tend to differ in this case. In particular, profits tend to lose the hump-shaped response, which instead appears in the response of Q. The former is likely to be due to the smaller increase in sales personnel in response to an aggregate shock, and the latter the changes in discounting. The theory would thus imply that while customer base concerns may help explain the failure of investment-Q regressions in the cross section, it is less clear it could do so in the time series.

4 The Evidence for Customer Capital

Although we view customer base concerns as relevant for most firms, some markets are likely to be more affected than others. This suggests evaluating the model's predictions empirically by sorting markets according to a proxy for the importance of customer capital, and comparing the patterns implied by the model across markets.

[10] Alternative explanations include measurement error (Erickson and Whited 2000) or a combination of nonlinear shocks and decreasing returns (Eberly, Rebelo, and Vincent 2008).

Measuring Customer Capital Our primary data source is Compustat, commonly used in studies of investment and firm dynamics, which provides accounting data for publicly listed US firms. The model associates customer capital with frictions in product evaluation, a process which requires firms to spend resources on sales personnel and exhibits convex costs hindering firm expansion. These frictions also naturally lead customers to stay with the same firm for a period of time, leading to customer accumulation over time. If one could thus measure the extent of these costs across industries, this would provide a useful proxy for the importance of customer base concerns in these markets, to sort industries with.

To this end, Compustat offers two potentially useful measures of selling expenses, each with some drawbacks. The first is advertising expenses. This measure has the advantage that we would expect high advertising to be associated with a desire to expand sales. The drawbacks are that: first, it is not immediate to what extent advertising expenses are associated with broader selling expenses, and second, advertising data are only available for a limited set of firms/years. The second measure is total selling, general and administrative (SGA) expenses. This measure has the advantage that it covers a broader set of selling expenses than just advertising alone, such as marketing expenses and the salaries and commissions of sales personnel. The drawback is that it includes also other overhead variables, which do not play a role in our theory. Within the subset of firms reporting both, the cross-sectional correlation between firm level advertising and SGA is 0.35, while the time series correlation between the two is 0.41. With these concerns in mind, and because the SGA variable is much more broadly reported, we focus on it rather than advertising expenses in what follows.

We partition the Compustat data by industry as follows: for each 2-digit SIC industry, we calculate average selling expenses as the time series average of the ratio of total industry SGA expenses to total industry sales. We then split the full sample into two subsamples - industries with above and below median average selling expenses - and look for evidence of the predictions of our theory in these samples. Additional information on the industries falling into the two samples is provided in the Appendix. Consistent with intuition, commodities, for which customer base concerns are likely to play a smaller role, fall into the lower selling expense group, while tobacco products and clothing retailers are examples of high selling

expense industries.

In what follows, we restrict our analysis to a balanced sample of 651 firms over 1984-1999, or 16 years. The balanced sample significantly simplifies the analysis of firm-level dynamics, but the results are largely robust to extending, where possible, the sample to the full unbalanced Compustat data. We exclude utilities and financial firms, as is commonly done in the investment literature, as well as mergers and observations with extreme values for the investment and profit rates.

Table 2: Comparing the low and high SGA samples

Median	Low SGA	High SGA
SGA/Sales	0.160	0.270
ADV/Sales	0.017	0.032
I/K	0.103	0.111
PI/K	0.210	0.303
Q	1.010	1.653
Sales/ProdCost	1.373	1.608

Notes: This table reports the median (across firms and across time) of some accounting ratios, for the low SGA sample, and for the high SGA sample. The accounting ratios are SGA over sales, advertising expenses over sales, investment over capital, profits (operating income before depreciation, taxes and interest) over capital, Tobin's Q, and the ratio of sales to production costs i.e. cost of goods sold.

Levels The first set of predictions from the model involves level effects, compared across the two samples in Table 2. Beginning with our proxy for selling expenses, the first row shows that there is a substantial difference in SGA expenses to sales across the two samples. The share of advertising expenses is also significantly larger in the high SGA sample, supportive of the view that the high SGA sample reflects higher selling expenses.[11] The figures also reveal that advertising expenses are much smaller than total SGA, a finding which seems quite natural if one thinks about the broader costs of marketing and sales personnel for the firm.

The model predicts that in industries where firms incur higher selling expenses, we should observe higher profit rates, higher Tobin's Q, as well as higher markups. The table shows significant evidence of these patterns in the data: the profit rate is about 50% greater,

[11]To compute this statistic, we need to restrict the sample to those observations for which advertising data is available, leading to a smaller sample.

Tobin's Q over 60% greater, and markups about 20% greater in the high SGA sample. The empirical measure of markup is admittedly a crude one – the ratio of sales over production cost[12] – as the latter measures average, rather than marginal, production costs. Despite this, the numbers line up with our theory. Finally, the theory predicts that investment rates should equal the depreciation rate on physical capital across the two samples. The third row of the table confirms that investment rates are indeed similar across the two samples.

Firm Level Shocks The second set of predictions from the model involve firm responses to shocks. This section studies these responses at the micro-level, where idiosyncratic shocks dominate, while the next section considers more aggregate data. First, we would expect firms to respond less to a given shock in the high SGA sample than in the low SGA sample. Table 3 presents the evidence on firm level volatility both in absolute terms and relative to the volatility of Tobin's Q. Contrary to the prediction of the model, these volatilities appear to be higher in the high SGA sample. However, our simple volatility measure cannot distinguish between a more volatile fundamental shock process, and different responses to shocks of a given size. (The model makes no predictions about the incidence of idiosyncratic shocks across the two samples.) We therefore need to scale these results by the volatility of the shock, which is difficult to measure.

Using the model to shed light on this points to using Tobin's Q as a proxy for the shocks, because it both responds to shocks on impact and is relatively straightforward to measure given the available data. As existing literature further supports the view that *firm level* variation in Tobin's Q is informative about *firm level* variation in profitability, we proceed to use Tobin's Q as a proxy for firm level shocks.[13]

The left columns of Table 3 show that the volatilities of investment, profits and sales are all significantly lower in the high SGA sample, once we scale these volatilities by the volatility of Q. This provides support for the model mechanism.[14]

[12] cost of goods sold

[13] Vuolteenaho (2002) shows that cross-sectional variation in Q is, in large part, driven by variations in expected future cash flows, which suggests that our approach is reasonable for firm level variation, even if not for aggregate level variation.

[14] Based on the model, one would also expect the customer expansion friction to contribute toward greater persistence of sales or investment in the high SGA sample. There is some limited evidence for these patterns.

Table 3: Firm level time series volatility in the low and high SGA samples

	relative to Q		absolute	
Std. dev.	Low SGA	High SGA	Low SGA	High SGA
I/K	0.133	0.073	0.065	0.062
PI/K	0.172	0.135	0.085	0.115
Q	1	1	0.492	0.847
Sales/ProdCost	0.125	0.112	0.062	0.095
Sales/K	0.868	0.652	0.427	0.552

Notes: This table reports, for both the low and high SGA sample, the median (across firms) of the time-series standard deviation of the investment rate, the profit rate, our measure of markup, and the sales-capital ratio.

Figures 5 and 6 consider the timing of firm responses, correlating firm level data on investment with firm level Tobin's Q and SGA. Recall that if product markets were entirely frictionless, the neoclassical adjustment cost model would imply that Tobin's Q equals marginal Q, with investment perfectly correlated with contemporaneous Tobin's Q. Under frictional product markets the correlations shift toward lagged values of Tobin's Q instead, as the firm must first invest in customer capital. Figure 5 shows that investment indeed tends to be correlated with past values of Tobin's Q, as the model would suggest. In particular, the figure shows that this lag pattern is stronger for the high SGA sample.[15] Note that the figure is based on annual data, so the lags displayed are quite substantial. Figure 6 sheds light on the response of SGA to the shock, showing that: i) SGA has a higher correlation with investment in the high SGA sample, and ii) SGA tends to lead investment overall. The fact that SGA leads investment is a direct prediction of our model. By contrast, sales themselves hardly lead investment.

Finally, we turn to the implications for the investment-Q regressions, which have attracted much attention in the empirical investment and finance literatures. Table 4 presents the

[15]Time-to-build can also give rise to lead-lag patterns, but the basic prediction of time-to-build is to make investment dependent on leads of Tobin's Q rather than lags, because in that environment investment decisions reflect the future value of capital. Time-to-plan would have the opposite effect, providing a potential explanation for the overall lag pattern in the data, but the differential timing in the two samples supports our theory.

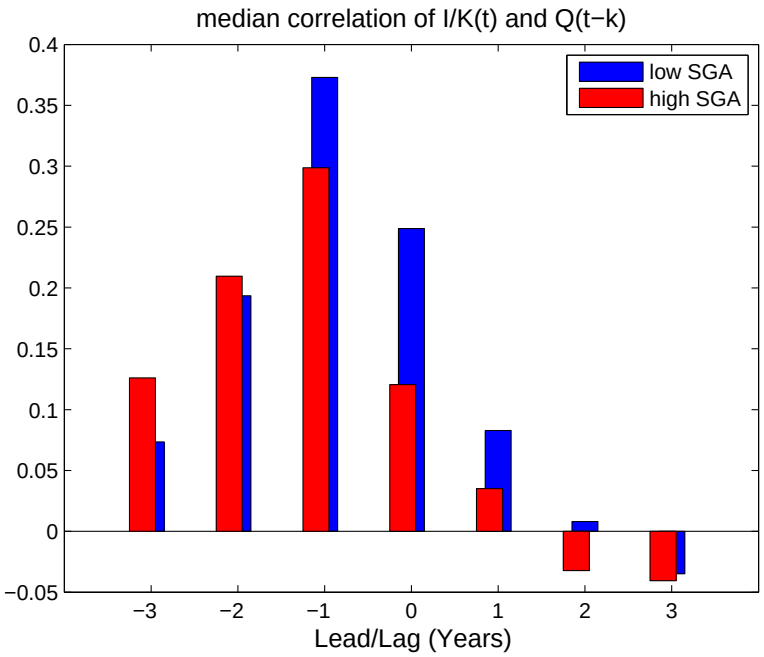


Figure 5: Cross-correlogram of investment rate and Tobin's Q

Notes: For each sample, and for each lead or lag, we compute the median across firms of the time-series cross-correlation.

results from running the regressions

$$\frac{I_{i,t}}{K_{i,t-1}} = b_0 + b_1 Q_{i,t-1} + f_t + d_i + \varepsilon_{i,t}, \tag{14}$$

$$\frac{I_{i,t}}{K_{i,t-1}} = b_0 + b_1 Q_{i,t-1} + b_2 \frac{CF_{i,t-1}}{K_{i,t-1}} + f_t + d_i + \varepsilon_{i,t}, \tag{15}$$

in each of the two samples, with and without firm fixed effects.[16] The results line up well with the theory: in industries with higher selling expenses, the coefficient on Q is significantly lower, the coefficient on cash flow significantly higher, and the R^2 lower. Moreover, these results appear robust to changes in the definition of Q, changes in the timing and specification of the regressions (levels vs. logs), as well as the exclusion of firm fixed effects.[17]

In thinking about the relationship between these findings and the investment literature, one concern may be that the two samples of industries contain very different types of firms,

[16] Note that we follow the standard timing of investment regressions in the empirical literature, i.e. we use the lagged values of the profit rate and Tobin's Q. This is in contrast to the model regressions which were run with the timing which is correct in the model.

[17] The appendix presents results for some alternative specifications.

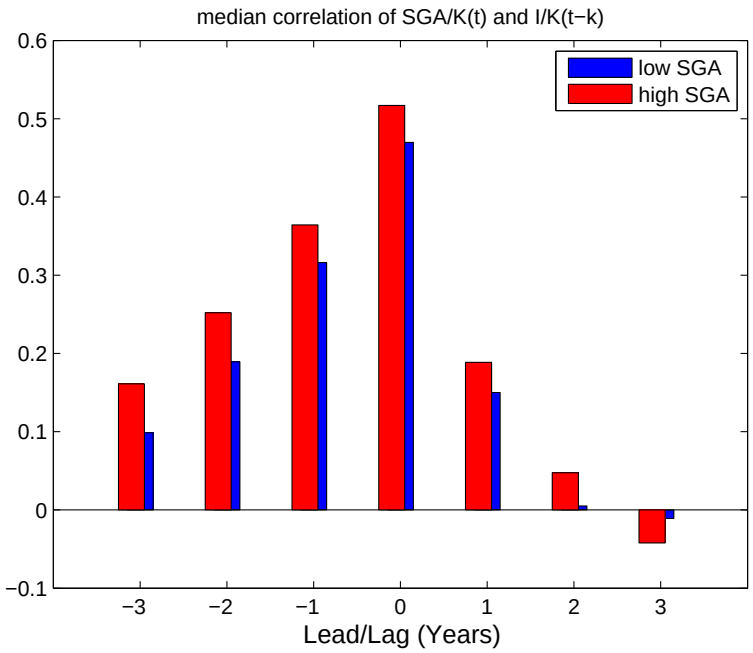


Figure 6: Cross-correlogram of investment rate and SGA over capital

Notes: For each sample, and for each lead or lag, we compute the median across firms of the time-series cross-correlation.

and that these differences drive our results. To gauge this potential concern we also ran the regressions restricting the sample to manufacturing firms only. As Table 5 shows, the regression results continue to hold in this restricted sample.[18]

The empirical finance literature often associates the failure of investment-Q regressions with financial constraints on firms, arguing that such constraints are responsible for the poor performance of the regressions. A potential concern with our results would thus be that the high SGA firms could simply be firms which are particularly affected by financial constraints. This story seems plausible because the intangible capital embodied in the customer base is less likely to serve as collateral than physical capital. High customer capital firms might thus naturally have a lower ability to borrow. Comparing firms in the two samples, it turns out that the high SGA firms indeed have slightly less debt than the low SGA firms: the average value of debt to total assets is 0.18 for low SGA firms, while only 0.16 for high SGA firms. Comparing the samples in terms of dividend payout does not support this story, however,

[18]Recall that, as mentioned previously, the share of manufacturing firms is in fact greater in the high SGA sample than the low SGA sample.

Table 4: Investment-Q regressions

	Low SGA				High SGA			
Coeff.	1a	2a	3a	4a	1b	2b	3b	4b
Q	.044	.041	.033	.031	.028	.025	.021	.019
s.e.	.001	.002	.001	.001	.001	.001	.001	.001
CF/K	–	.030	–	.039	–	.043	–	.047
s.e.	–	.006	–	.004	–	.003	–	.002
R^2	0.159	0.169	0.091	0.099	0.153	0.162	0.087	0.115
Fixed effects	y	y	n	n	y	y	n	n

Table 5: Investment-Q regressions for manufacturing

	Low SGA				High SGA			
Coeff.	1a	2a	3a	4a	1b	2b	3b	4b
Q	.038	.034	.032	.029	.028	.024	.022	.020
s.e.	.002	.002	.001	.001	.001	.001	.001	.001
CF/K	–	.040	–	.050	–	.043	–	.043
s.e.	–	.008	–	.006	–	.004	–	.003
R^2	0.193	0.194	0.137	0.154	0.153	0.169	0.100	0.125
Fixed effects	y	y	n	n	y	y	n	n

because the high SGA firms distribute more in dividends: while the average dividend to total assets ratio is 0.013 for the low SGA sample, it is 0.017 for the high SGA sample. The share of firms paying dividends is also higher in the high SGA sample: 79 percent relative to the 75 percent in the low SGA sample. Overall, it does not seem likely that financial frictions are driving our results. This is not surprising since our sample is dominated by large firms which are less likely to be borrowing constrained.

Aggregate Shocks In the same way as we examined the model's predictions in response to firm level shocks in the two samples, we can also examine them in response to aggregate shocks. Incorporating aggregate productivity shocks into the model renders both investment in physical capital and investment in customer capital procyclical. Figure 7 displays the corresponding patterns in the data, aggregating up the firm level data from Compustat on investment and SGA. While procyclical, this proxy for investment in customer capital is clearly less variable than investment in physical capital.

Table 6 begins with the volatilities of annual growth rates, averaged across firms. The

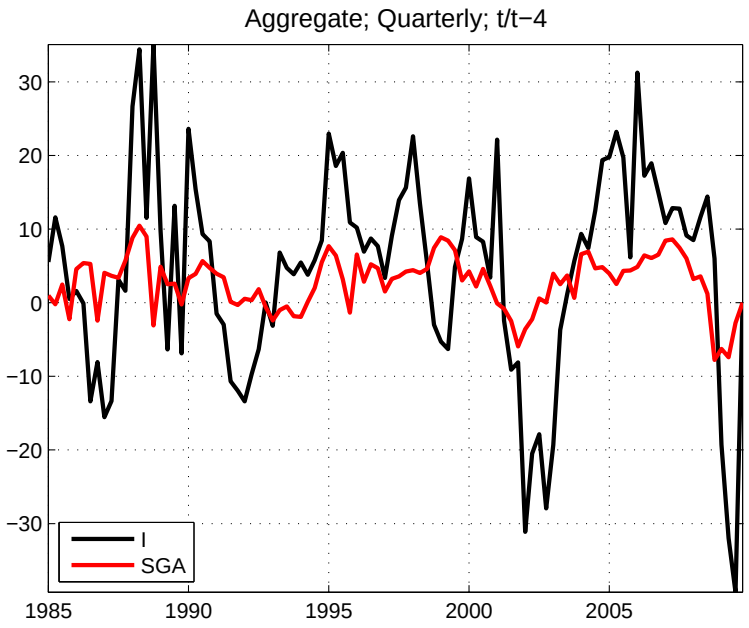


Figure 7: Growth rate of aggregate investment and SGA
Notes: Quarterly data from Compustat, 1984:Q1-2009:Q4.

table shows lower variability in the high SGA sample – perhaps surprising given the higher prevalence of manufacturing firms in this sample. This finding is consistent with our theory, at least if one views all firms as being hit by the same aggregate shock process. Scaling the volatilities by the volatility of Q would not change our results in this case.[19]

Our model implies lagged responses of variables to a TFP shock. To study this pattern, we measure TFP growth using NIPA data, and run regressions of cumulated future growth of either GDP, or aggregated sales, investment and SGA from Compustat, on this TFP growth.[20] Figure 8 presents the results. The figure suggests hump-shaped responses of investment and GDP, as the total response peaks after 2-3 quarters. Interestingly, SGA responds faster than investment, as our model would imply.

Finally, a basic implication of our model is that SGA should lead investment. Figure 9

[19]In the same way we would expect high SGA industries to exhibit lower volatility, we might expect them to exhibit higher persistence in responses. In the data, however, we find little difference between the two samples.

[20]The results are nearly identical if we fit an AR(1) to TFP, compute the shock as the residual, and run the macro variables on the shock.

Table 6: Standard deviations of average annual growth rates

Time series st. dev.	Low SGA	High SGA
sales	6.063	3.299
investment	11.288	8.305
SGA	3.611	3.157
profit1	18.063	10.175
profit2	11.020	6.728
production cost	6.273	3.327
advertising	7.796	7.892
firm value	16.934	14.848
markup	1.406	1.033

Notes: This table reports, for both the low and high SGA sample, the standard deviation of the aggregate growth rate of each variable. Aggregates are constructed by summing across each sample. The growth rates are calculated using quarterly data, 1984-2009, by constructing the growth rate over the same quarter over the previous year, and deflating using the PCE or investment deflator.

produces the cross-correlogram of investment and SGA, using aggregate time series data for each of the two samples. There is a clear difference between the two samples, with SGA leading clearly investment in the high friction sample, while the relation is almost inverted in the low friction sample.

5 Concluding Remarks

We believe the model has interesting implications beyond those explored in this paper. For example, a number of recent papers have proposed news shocks as a potentially important driver of business cycles (Beaudry and Portier 2004, Beaudry and Portier 2006, Jaimovich and Rebelo 2009). Introducing news shocks creates tensions between the predictions of the neoclassical growth model and business cycle data, however, which have required these authors to introduce additional features into the model to reconcile the two. Specifically, in the model good news about future productivity tend to lead to a drop in hours worked – instead of the increase one would expect during an economic expansion. Customer base concerns offer one way to reconcile the model and data, because good news about future productivity cause firms to start building up their customer base in advance, leading to an increase in hours worked both in production and sales.

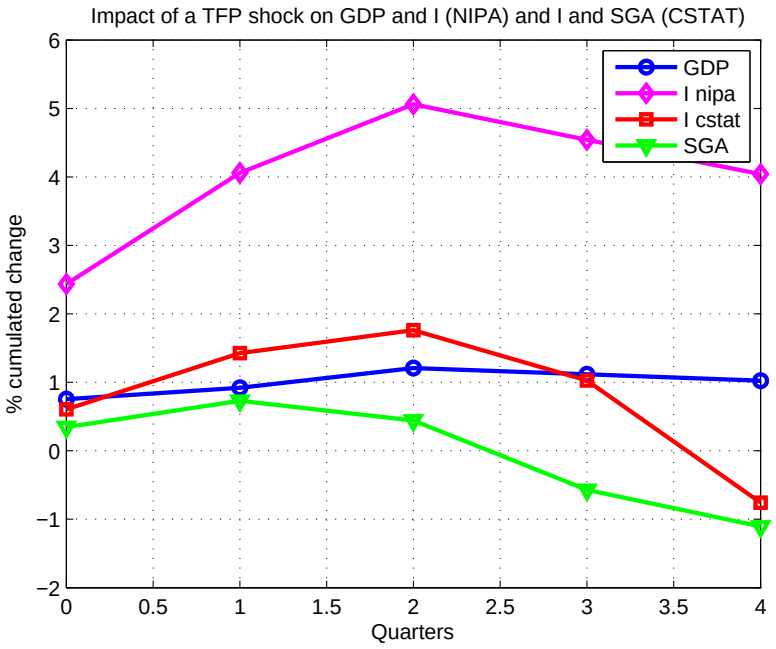


Figure 8: Responses of aggregate variables to TFP

Notes: Quarterly data from Compustat, 1984:Q1-2009:Q4. The figure shows the slope coefficient from the regression of $log(X_{t+k}/X_{t-1})$ on $log(TFP_t/TFP_{t-1})$, where X refers to aggregated GDP, investment or SGA.

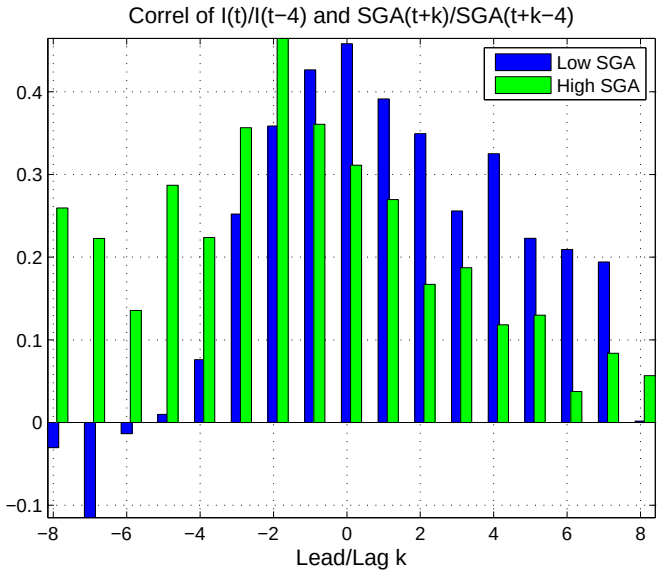


Figure 9: Cross-correlogram of aggregate investment growth and aggregate SGA growth

Notes: Quarterly data from Compustat, 1984:Q1-2009:Q4.

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Data Appendix

Selling, General and Administrative expenses (SGA):

Selling expenses: represent expenses needed to sell products (e.g. salaries of sales people, commissions and travel expenses, advertising, freight, shipping, depreciation of sales store buildings and equipment, etc.).

General and Administrative (GA) expenses: represent expenses to manage the business (salaries of officers / executives, legal and professional fees, utilities, insurance, depreciation of office building and equipment, office rents, office supplies, etc.).

The industries falling into the high and low SGA categories are listed in tables 7 and 8.

Table 7: High SGA

Division A: Agriculture, Forestry, And Fishing
- Major Group 07: Agricultural Services

Division D: Manufacturing
- Major Group 20: Food And Kindred Products
- Major Group 21: Tobacco Products
- Major Group 23: Apparel And Other Finished Products Made From Fabrics And Similar Materials
- Major Group 27: Printing, Publishing, And Allied Industries
- Major Group 28: Chemicals And Allied Products
- Major Group 31: Leather And Leather Products
- Major Group 35: Industrial And Commercial Machinery And Computer Equipment
- Major Group 38: Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Wat
- Major Group 39: Miscellaneous Manufacturing Industries

Division G: Retail Trade
- Major Group 56: Apparel And Accessory Stores
- Major Group 57: Home Furniture, Furnishings, And Equipment Stores
- Major Group 59: Miscellaneous Retail

Division I: Services
- Major Group 73: Business Services
- Major Group 75: Automotive Repair, Services, And Parking
- Major Group 76: Miscellaneous Repair Services
- Major Group 81: Legal Services
- Major Group 82: Educational Services
- Major Group 84: Museums, Art Galleries, And Botanical And Zoological Gardens
- Major Group 86: Membership Organizations
- Major Group 89: Miscellaneous Services

Table 8: Low SGA

Division A: Agriculture, Forestry, And Fishing
- Major Group 01: Agricultural Production Crops
- Major Group 02: Agriculture production livestock and animal specialties
- Major Group 08: Forestry
- Major Group 09: Fishing, hunting, and trapping

Division B: Mining
- Major Group 10: Metal Mining
- Major Group 12: Coal Mining
- Major Group 13: Oil And Gas Extraction
- Major Group 14: Mining And Quarrying Of Nonmetallic Minerals, Except Fuels

Division C: Construction
- Major Group 15: Building Construction General Contractors And Operative Builders
- Major Group 16: Heavy Construction Other Than Building Construction Contractors
- Major Group 17: Construction Special Trade Contractors

Division D: Manufacturing
- Major Group 22: Textile Mill Products
- Major Group 24: Lumber And Wood Products, Except Furniture
- Major Group 25: Furniture And Fixtures
- Major Group 26: Paper And Allied Products
- Major Group 29: Petroleum Refining And Related Industries
- Major Group 30: Rubber And Miscellaneous Plastics Products
- Major Group 32: Stone, Clay, Glass, And Concrete Products
- Major Group 33: Primary Metal Industries
- Major Group 34: Fabricated Metal Products, Except Machinery And Transportation Equipment
- Major Group 36: Electronic And Other Electrical Equipment And Components, Except Computer Equipment
- Major Group 37: Transportation Equipment

Division E: Transportation, Communications, Electric, Gas, And Sanitary Services
- Major Group 40: Railroad Transportation
- Major Group 41: Local And Suburban Transit And Interurban Highway Passenger Transportation
- Major Group 42: Motor Freight Transportation And Warehousing
- Major Group 44: Water Transportation
- Major Group 45: Transportation By Air
- Major Group 46: Pipelines, Except Natural Gas
- Major Group 47: Transportation Services
- Major Group 48: Communications

Division F: Wholesale Trade
- Major Group 50: Wholesale Trade-durable Goods
- Major Group 51: Wholesale Trade-non-durable Goods

Division G: Retail Trade
- Major Group 52: Building Materials, Hardware, Garden Supply, And Mobile Home Dealers
- Major Group 53: General Merchandise Stores
- Major Group 54: Food Stores
- Major Group 55: Automotive Dealers And Gasoline Service Stations
- Major Group 58: Eating And Drinking Places

Division I: Services
- Major Group 70: Hotels, Rooming Houses, Camps, And Other Lodging Places
- Major Group 72: Personal Services
- Major Group 78: Motion Pictures
- Major Group 79: Amusement And Recreation Services
- Major Group 80: Health Services
- Major Group 83: Social Services
- Major Group 87: Engineering, Accounting, Research, Management, And Related Services

Division J: Public Administration
- Major Group 99: Nonclassifiable Establishments

Table 9: Summary statistics

	overall	low SGA	high SGA
I/K	0.107	0.103	0.111
PI/K	0.243	0.210	0.303
S/K	2.217	0.210	0.303
Q	1.218	1.010	1.653
SGA/S	0.201	0.160	0.270
SGA/K	0.426	0.160	0.270
ADV/S	0.022	0.017	0.032
ADV/K	0.050	0.034	0.081
S/COGS	1.449	1.373	1.608
Assets	305.760	281.776	346.816
Sales	413.019	366.346	491.115
Mkt value	242.540	197.955	338.117
Debt/Assets	0.170	0.180	0.156
Debt/Cap	0.170	0.180	0.156
Div/Earnings	0.098	0.088	0.113
Div/Assets	0.014	0.013	0.017

The share of manufacturing firms is 71.9% overall, but 62.4% in low SGA and 86.7% in high SGA. The share of firms paying dividends is 76.1% overall, but 74.5% in low SGA and 78.5% in high SGA.

Table 10: Regression of I/K on Q

	Simple regression		Time effects		Fixed effects		Both effects	
	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA
b_1	0.0324	0.0200	0.0331	0.0213	0.0452	0.0294	0.0435	0.0283
	(0.000953)	(0.000668)	(0.000963)	(0.000676)	(0.00146)	(0.001000)	(0.00145)	(0.000997)
R^2	0.080	0.060	0.091	0.087	0.155	0.129	0.159	0.153

Table 11: Regression of I/K on Q and PI/K

	Simple regression		Time effects		Fixed effects		Both effects	
	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA
b_1	0.0298	0.0181	0.0305	0.0193	0.0425	0.0259	0.0412	0.0249
	(0.00101)	(0.000664)	(0.00102)	(0.000674)	(0.00158)	(0.00105)	(0.00158)	(0.00106)
b_2	0.0398	0.0500	0.0385	0.0469	0.0341	0.0454	0.0302	0.0431
	(0.00387)	(0.00231)	(0.00386)	(0.00229)	(0.00567)	(0.00344)	(0.00571)	(0.00342)
R^2	0.089	0.093	0.099	0.115	0.159	0.141	0.169	0.162

Table 12: Regression of I/K on Q: manufacturing

	Simple regression		Time effects		Fixed effects		Both effects	
	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA
b_1	0.0312	0.0210	0.0321	0.0222	0.0397	0.0280	0.0379	0.0275
	(0.00125)	(0.000858)	(0.00126)	(0.000870)	(0.00185)	(0.00127)	(0.00183)	(0.00128)
R^2	0.111	0.070	0.137	0.100	0.180	0.125	0.193	0.153

Table 13: Regression of I/K on Q and PI/K: manufacturing

	Simple regression		Time effects		Fixed effects		Both effects	
	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA	Low SGA	High SGA
b_1	0.0278	0.0195	0.0289	0.0206	0.0353	0.0248	0.0341	0.0243
	(0.00134)	(0.000846)	(0.00135)	(0.000861)	(0.00206)	(0.00134)	(0.00205)	(0.00136)
b_2	0.0532	0.0456	0.0499	0.0427	0.0465	0.0444	0.0400	0.0432
	(0.00565)	(0.00275)	(0.00557)	(0.00272)	(0.00757)	(0.00426)	(0.00756)	(0.00430)
R^2	0.131	0.099	0.154	0.125	0.182	0.138	0.194	0.169