Customer Driven Establishment Dynamics and Allocative Efficiency*

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Abstract

A common result from models of misallocation is that allocative efficiency is reflected in the correlation between size and productivity. But establishments start small which raises the question: how does the distribution of size have to evolve over the lifecycle to achieve allocative efficiency? Simply put, it must be that more productive establishments grow faster at the expense of less productive establishments. As evidence of this selection mechanism, I use establishment level data to construct cohorts of entrants and show that the spread of growth between fast and slow growing establishments is positively associated with higher exit rates. But unlike typical models that feature selection, I show that neither increases in input costs nor greater volatility are the force behind selection. To reconcile these facts, I present a model where the degree to which customers are willing to match with establishments who produce low quality goods introduces a new margin that affects selection. In the model, 60 per cent of changes in the intensity of selection come from changes in demand side behavior. To assess this new margin of selection, I recalibrate a parameter which controls the degree to which establishments can crowd out others for customers to match the slower fanning out in the evolution of the size distribution in Chile relative to the US. The model suggests that going from the US to Chile in this dimension would result in a 44 per cent loss in welfare.

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1 Introduction

In recent research, Haltiwanger et al. (2010) document an "up or out" pattern for young firms using the Longitudinal Business Database. Young firms face higher exit rates while young survivors grow relative faster than their older counterparts. This fact hints at a cutthroat-like selection process amongst entrants, with only the best entrants growing while the rest exit. If the "up or out" pattern were indicative of such a selection mechanism, data over time and across industries should reveal a positive relationship between exit rates and the growth of young firms. Cohorts born into industries or periods with more intense selection pressure would be marked by higher thresholds for survival. Loosely speaking, establishments would need to grow faster, by accumulating resources from others in order to escape the hazard of exit.

Alternatively, there are equally valid explanations for a negative relationship between the growth of young establishments and exit rates. For instance, industries that are in the process of growing are by definition, expanding the market. Establishments in a growing industry are not competing for resources such as customers, but instead growing the market together. Hence growth in an expanding market need not be rivalrous, implying that growth rates of young establishments may be negatively related to exit rates. Similarly, Hsieh and Klenow (2011) use data from the US Manufacturing Census to show that productivity growth may be linked with the growth of young establishments. If growth in an industry is driven by productivity growth common to all, we should expect to see most establishments growing and potentially lowering the likelihood of exit. That is, a weakly negative relationship as higher growth is coupled with lower exit rates among entering establishments. Under these two theories, growth of young establishments are not indicative of increased selection.

When constructing the data for the "up or out" pattern, growth of young firms is defined as the employment weighted average year-on-year growth in employment of survivors relative to older firms. However, this measure of growth conflates two very different forms of growth. Faster growth can be driven by a small number of rapidly growing firms with most other firms not growing at all or instead, a common growth rate for all entrants. The difference between these two different forms of growth is that the former is captured by the *difference* in growth rates between fast and slow growing firms, while the latter is captured by the *level* of growth rates. These two measures of the growth of young firms mirror the distinction between rivalrous growth and growing the market together. A larger spread in the growth of fast and slow growing firms captures rivalry in growth while the level of growth captures overall market growth.

The "up or out" pattern established thus far is literally a single data point, so it is uninformative about the relative roles of rivalrous and common growth in determining exit rates. In this paper, I use establishment-level data to uncover the relationship between exit rates and these two measures of the growth of young establishments. The data show that both forms of growth are closely linked to exit rates of young establishments, with an increase in the measure of rivalrous growth and a decrease in the measure of common growth leading to greater exit of young establishments. I interpret these facts as evidence that rivalry in growth and common-to-all growth both matter in understanding the growth patterns of young establishments.

In particular, I use time series variation within 3 digit (SIC) manufacturing industries to establish these facts for young establishments. A 10 per cent increase in the spread of growth of fast and slow growing establishments is associated with at 1.5 per cent increase in exit rates. To put this in perspective, going from the 10th percentile observation in terms of this measure of the spread to the 90th percentile observation would entail a 27 per cent increase in exit rates. The effect from the level of growth goes in the opposite direction, but is much larger. A 10 per cent increase in the level of growth decreases exit by 4.1 per cent, with the 10th-90th percentile variation generating a 39 per cent decrease in exit. Both coefficients are statistically significant and control for year effects and fixed effects at the industry level.

However, in contrast to selection mechanisms that typically characterize models of heterogeneous establishments, stronger selection does not appear to be achieved through increases in factor prices. Industries which experienced an increase in the strength of selection, as defined by periods where there was an increase in the spread of growth and an increase in exit rates, did not experience a corresponding rise in wages. This is in stark contrast to dynamics in typical models of heterogeneous establishments when distortions or frictions are weakened.[1] The reallocation of resources towards more productive establishments increases the marginal product of factors, increasing factor prices and inducing exit of less productive establishments as they become unprofitable.

Instead, I focus on the response by customers in inducing exit. Since product markets are characterized by search frictions, customers often satisfice by accepting a less than desirable match to avoid the costly nature of search. The degree to which customers are willing to satisfice is a margin which affects selection. When customers believe the likelihood of a good match has increased or equivalently, the expected time until a good match will arise shortens, they satisfice less and reject matches with establishments they would have previously matched with. Hence selection forces can strengthen without corresponding increases in factor prices.

Understanding the growth of young establishments is important as entering establishments account for a significant proportion of productivity growth. Foster et al. (2008) use data on physical measures of inputs and outputs in a subset of manufacturing industries to show that just under a quarter of productivity growth is due to entry of new establishments. As is typical in the misallocation literature, the allocation of production across establishments directly affects allocative efficiency. The difference here is that establishments must match with customers

[1] Anything that reallocates production to relatively productive establishments will lead to an increase in factor prices.

instead of selling their output in spot markets. When customers are allocated inefficiently, production is reallocated to lower quality establishments, lowering welfare.[2] Hence spreads in growth rates between fast and slow growing establishments may be informative regarding allocative efficiency. An economy that can allocate the bulk of its customers to establishments producing high quality goods will be characterized by slower growth of establishments in the left tail of the quality distribution and much faster growth for those establishments in the thinner right tail.

As a cross country comparison, I compute the spread in growth rates between fast and slow growing establishments in the US and Chile. After 10 years, the 90th percentile (in terms of cumulative growth of employment) surviving Manufacturing establishment in the US has added 6.74 median establishments more worth of workers than the median 10 year old establishment while the spread in cumulative growth is only between 2.09-3.17 in Chile. In other words, the evolution of the cumulative growth distribution for entering manufacturing establishments fans out much more rapidly in the US than in Chile. Of course, it is unlikely that the difference in spreads is caused entirely by differences in allocative efficiency but this simply implies that inferences drawn from these differences should be interpreted as upper bounds.

To assess the quantitative effect of such a difference in the spread of growth rates on aggregates and the role of customers in driving selection, I construct a model with features that mimic the data. Entrants start small and need to accumulate customers in order to grow. Increasing the degree to which establishments can crowd out others for customers raises growth rates in the thin right tail of highly productive entrants while slowing down growth of other establishments, leading to higher exit rates of young establishments. Moreover, as in the data, resources are continually being reallocated via endogenous entry and exit from incumbents to entrants, who have higher quality on average.

In the model, establishments match randomly with customers via marketing efforts which increase a given establishment's own rate of matching, while decreasing other establishments rate of matching. The degree to which establishments can crowd out other establishments for customers matters for allocative efficiency, since the allocation of customers reflects the allocation of production. An increase in the extent to which establishments can crowd out others is beneficial for establishments producing higher quality goods since they utilize marketing efforts relatively more than lower quality establishments. Hence the gap in both marketing efforts and growth between high and low quality establishments increases as crowding out becomes easier. High quality producers find it easier to accumulate customers leading production to shift toward these establishments improving allocative efficiency.

As stated earlier, the extent to which establishments can crowd out others affects customers

[2] Although quality can alternatively be interpreted as productivity, the point here is that growth need not be correlated with productivity and supply side considerations. Instead, I focus on an environment with homogeneous goods that are produced at different qualities.

expectations about matching. When crowding out becomes easier, customers' expected value from a match increases as the likelihood of matching with an establishment producing high quality goods is raised. Hence customers shun matches they would previously accept, in favor of returning to search. This raises the exit threshold, shortening the lifespan of all establishments and undoing part of the gains from improved allocative efficiency.

Both these margins provide a link between the ability of high quality establishments to accumulate rivalrous resources and allocative efficiency. I calibrate the baseline model to a rich set of stylized facts on manufacturing establishments in the US and assess the effect on allocative efficiency from a decrease in the ability of establishments to crowd out other establishments. To discipline the magnitude of this change, I match the slower fanning out of the cumulative growth distribution observed in Chile by reducing the ability of establishments to crowd out others for customers. Welfare falls by between 29 to 45 per cent as production is reallocated towards less lower quality producers reflecting less allocative efficiency. Using a simple decomposition, I find that 60 per cent of the weakening in selection is due to changes in customer behavior.

1.1 Related literature

The paper is most closely related to Hsieh and Klenow (2011) in that it focuses on manufacturing establishment growth and aggregate productivity. Here, I focus on the evolution of the size distribution over the lifecycle and the role of customers in driving selection and allocative efficiency, instead of productivity growth. Two key margins affect allocative efficiency: the reallocation of resources to entrants via entry and exit and rivalrous allocation of resources across entrants. In contrast, Hsieh and Klenow (2011) is concerned with mean productivity growth over the lifecycle in determining aggregate productivity as opposed to allocative efficiency. As productivity is proportional to labor, the critical statistic in their model is the evolution of mean size over the lifecycle. Here, the model is agnostic regarding mean growth over the lifecycle while suggesting that a greater "fanning out" of the cumulative growth distribution over the lifecycle is evidence of higher allocative efficiency.

Within the strand of literature on firm or establishment growth, the process of establishment growth used in this paper is most closely related to Fajgelbaum (2011) who studies the effect of labor market frictions on export or technology adoption decisions via the constraint on firm growth. Firms hire workers subject to labor market search frictions until they have accumulated enough labor to make a once-off investment in exporting or technology adoption. The mechanism here is firms' rivalrous accumulation of customers, which affects both the allocation of workers across entrants and reallocation towards entrants via entry and exit.

The mechanism of growth is also similar to Gourio and Rudanko (2011) and Dinlersoz and Yorukoglu (2012) where customer accumulation is the key channel of firm growth. Both papers introduce customers as a form of capital but for different purposes. Gourio and Rudanko (2011) focus on the sluggish nature of adjustment in customer capital which affects firms responses to shocks while Dinlersoz and Yorukoglu (2012) explore the role of information dissemination in attracting customers. In contrast, the model here features customer accumulation as the channel of rivalrous growth to explore allocative efficiency across heterogeneous establishments and the role of demand side considerations in selection.[3]

Models of establishment size or growth rates can broadly be categorized as relying on either exogenous characteristics that persist through the lifecycle (such as productivity in Hopenhayn (1992) and the likelihood of particular productivity draws Atkeson and Kehoe (2005)) or the accumulation of some resource (blueprints in Luttmer (2011) and knowledge capital in Atkeson and Burstein (2010)). Establishment growth in this paper relies on the accumulation of resources which are easier to accumulate for establishments born with a technology to produce relatively high quality goods.

The rest of the paper is organized as follows. In Section 2, I describe the data and document 3 stylized facts about establishment dynamics. The complete model is developed in Section 3. Section 4 describes the calibration and estimation strategy applied to US data. The results, which include the calibration to Chilean data and the subsequent effect on aggregates, are presented in Section 5. Finally, I conclude in Section 6.

2 Data

The data in this section are from the US Census Bureau's Synthetic Longitudinal Database (LBD) and the National Statistics Institute (INE) of Chile's Annual Manufacturing Census (ENIA). The synthetic LBD contains synthetic data between 1976 and 2000 created from the confidential version of the Census Bureau's LBD. Statistical models are fit to the data in the confidential LBD and then simulated to create the synthetic LBD (Kinney et al., 2011). Since the data is synthetic, there are obviously aspects of the data that the synthetic LBD will not capture, regardless of how comprehensive the statistical models used to create the synthetic data. However, in the dimensions explored in this paper, the synthetic LBD is representative of the confidential LBD as the results in this paper have been analytically validated. Hence aside from negligible quantitative differences, the results may as well have come from the confidential version of the LBD.

The confidential LBD contains longitudinal data on all establishments on the Census Bureau's Business Register, a large list developed and maintained for the purpose of all federal statistical agencies (Jarmin and Miranda, 2002). The LBD is a particularly useful dataset for studying the dynamics of young establishments as the annual frequency and longitudinal nature of the

[3] In the model, customers can alternatively be interpreted as skilled labor where production is Leontief in skilled and unskilled labor.

data allows cohorts of establishments to be followed. For this paper, I focus on manufacturing establishments which are defined as those establishments with SIC code between 52 and 59.

Data on Chilean establishments are taken from the ENIA between 1995 and 2007. While there are less establishments in the sample and less years in the sample, the data on each establishment is much more detailed when compared with the LBD since the data come from a Manufacturing census. For example, detailed data on inputs used in the production process are available. The LBD is limited to industry code, payroll, employment and age for each establishment.

For each establishment in both samples, I calculate age as the time from when the establishment first appeared in the dataset. Therefore, for any calculation that requires the age of an establishment, I exclude establishments that first appeared in 1995 in the ENIA data and prior to 1976 from the LBD data since age is indeterminate for these establishments.

While both the LBD and ENIA samples both cover manufacturing establishments, they are not directly comparable. The ENIA excludes establishments that are (i) single-unit (not part of a firm with multiple factories) with less than 10 employees and (ii) part of a firm with less than 10 employees. In contrast, the LBD contains data on all establishments. Ideally, I would restrict the sample in the LBD on the same criteria as the LBD when directly comparing the two datasets. Although the synthetic LBD identifies establishments as being single unit or multi-unit (owned by a firm with more than one establishment), it does not contain parent or firm identifiers so it is not possible to identify firm size (as opposed to establishment size). Given these constraints, I exclude single-unit establishments with less than 10 employees but leave establishments which are multi-unit and part of firms with more than one establishment because firm size is not identified. Fortunately, the number of multi-unit establishments at firms with less than 10 employees is tiny so leaving these establishments in the sample will not affect the results.[4]

To account for scale issues between the countries, I divide cumulative growth by the median employment for each industry. This should eliminate effects from the much larger size of the US economy and scale effects from different industry composition across the two countries. Given these adjustments, I calculate the change in cumulative size (by employment) over the lifecycle relative to the median sized manufacturing establishment for each country.[5]

Even after constructing the samples to make them as comparable as possible, it is likely that the industry composition of the manufacturing sectors in each country are fundamentally different. One expects a higher proportion of establishments to be classified as high tech relative to establishments in Chilean manufacturing. Because industries are likely to differ in terms of

[4]According to data in the Census Bureau's Business Dynamics Statistics in 2010, multi-unit establishments at firms with less than 10 employees represent less than 0.05 per cent of all manufacturing establishments.

[5]The median establishment size in both countries is quite similar. Over their respective range of years, the median establishment size ranges from 27 to 30 workers in the US and 22 to 29 in Chile. Moreover, the median establishment size over the whole sample is 28 in the US compared to 24 in Chile.

optimal size and returns to scale, comparisons between Manufacturing in the US and Chile need to account for these differences. To do so, I attach sampling weights to Chilean establishments based on their 4 digit ISIC Revision 3.1 codes that re-weight the sample such that industry composition mirrors that in the US.[6] Hence the results that follow are not affected by differences in the composition of Manufacturing between the countries.

To summarize what follows, there are three new stylized facts that I observe in the data: (*i*) higher exit rates of young establishments are positively associated with larger spreads in growth between fast and slow growing establishments in the US, (*ii*) establishments that grow *relatively* slower exit at a faster rate and (*iii*) the right tail of the distribution of surviving establishments' cumulative growth fans out much faster in the US relative to Chile.

2.1 Rivalrous growth

As documented in Cabral and Mata (2003), the size distribution fans out over the lifecycle. Most establishments start small with the right tail dragging the median establishment rightwards over time. Here, I show that an increase in terms of the difference in cumulative growth of fast and slow growing establishments is associated with higher exit rates of young establishments. The measure of cumulative growth for an a-old establishment i, in industry j is

$$g_{a,i,j} = \frac{emp_{i,a} - emp_{i,0}}{median_{i'}\left(emp_{i',j}\right)}$$

For each 3 digit SIC industry in manufacturing, I need a measure of the spread or fanning out of the cumulative growth distribution and exit rates for young establishments. To do so, I construct cohorts of establishments born in the same year for each industry, calculate the statistic of interest for each cohort, and then take the mean over the cohorts. Alternative weighting schemes over the cohorts, such as entrant or employment weighted generate qualitatively similar patterns.

The exit rate for a particular industry is the average exit rate across the cohorts. That is, for every cohort in a given industry, I calculate the mean yearly exit rate for establishments aged 5 or less and then average across the cohorts. Similarly, for a given industry, I calculate percentiles of cumulative growth within each cohort up until age 5. Calculating percentiles within cohorts accounts for year effects at the industry level, since year effects will not distort relative growth within a cohort. For each cohort and at each age under 5, I then calculate the difference between the 80th and 50th percentile cumulative growth, accounting for exiters.[7] For example,

[6] In particular, I used the Census Bureau's ISIC 3.1 to 2002 NAICS concordance. The mapping between ISIC to NAICS codes are often many to many. Since there is no way to make this mapping one-to-one, I attach weights such that an establishment with an ISIC code with many NAICS correspondences is treated as a separate establishment for each NAICS correspondence with sampling weights reflecting each NAICS code's relative weight in the US compared to the other NAICS correspondences. This ensures that the composition of manufacturing in the adjusted ENIA sample mirrors that in the US.

[7] The identical calculation can be made only including survivors. However, this may mechanically generate a

I calculate the 50th-80th percentile spread for age 1, 2, ..., and 5 in a given cohort and then take the average of these spreads as a cohorts' value of the 50-80 spread. Finally, I take the average across the cohorts for each industry and am left with a 50-80 spread for each industry. So far, this calculation only uses the cross section for identification. To exploit the time dimension of the data, I perform the procedure above for without averaging over cohorts to generate a panel dataset where the cross sectional unit is an industry and new cohorts are born for each unit of time.

Figure 1 shows a scatter plot of this data. Each point represents an industry. There is a clear positive relationship between exit and the spread in cumulative growth of young establishments. However, the simple scatter plot analysis does not take into account fixed effects. Industries may have high exit rates for an entirely different reason that is correlated with larger spreads in cumulative growth. For example, it may be that an industries differ in their general level of competitiveness which is fixed over time yet correlated to larger spreads. In this case, it would be wrong to conclude that changes in the spread of cumulative growth would lead to changes in exit rates since the relationship is just identifying a relationship in the level of general competitiveness and exit rates.

To account for these fixed effects at the industry level, I estimate the relationship on differences instead of levels. This eliminates the role of any variable that is constant at the industry level and uses within industry variation to identify the effect of the spread in growth rates on exit rates of young establishments. In addition to the spread of cumulative growth, I include cumulative growth at the 65th percentile which should capture the effect of the level of cohorts' cumulative growth on exit rates and dummies for each year to account for year effects. I estimate the following equation using data on each industry j over the period 1976 to 2000 where u_j is the industry fixed effect eliminated by differencing.

$$\log\left(exit_{j,t}\right) = \left[\mathbb{I}_t \log\left(spread_{j,t}\right) \log\left(cumulativegrowth_{j,t}\right)\right]' \boldsymbol{\beta} + u_j + e_{j,t}$$

Table 1 displays the results of the estimation where reported standard errors are HAC robust. In all, there are 131-3 digit manufacturing industries representing 3259 industry-time pairs. The direction of each coefficient is consistent with the theory that the level of cumulative growth reflects growth of the cohort as a whole while the spread captures the growth of fast growing establishments relative to their slow growing counterparts. As the whole cohort grows, establishments are more likely to be performing well and hence less likely to exit. A larger spread in the relative performance of establishments, holding the level of growth across the cohort constant,

positive relationship between the spread in cumulative growth and exit. To see this, suppose exit disproportionally affects establishments that grow relatively slowly so that exit is essentially trimming the left tail of the distribution of cumulative growth. Higher exit is essentially larger truncation from the left. If the skewness of cumulative growth increases as you move rightwards along the distribution, then larger truncation from the left will mechanically increase skewness resulting in a positive relationship.

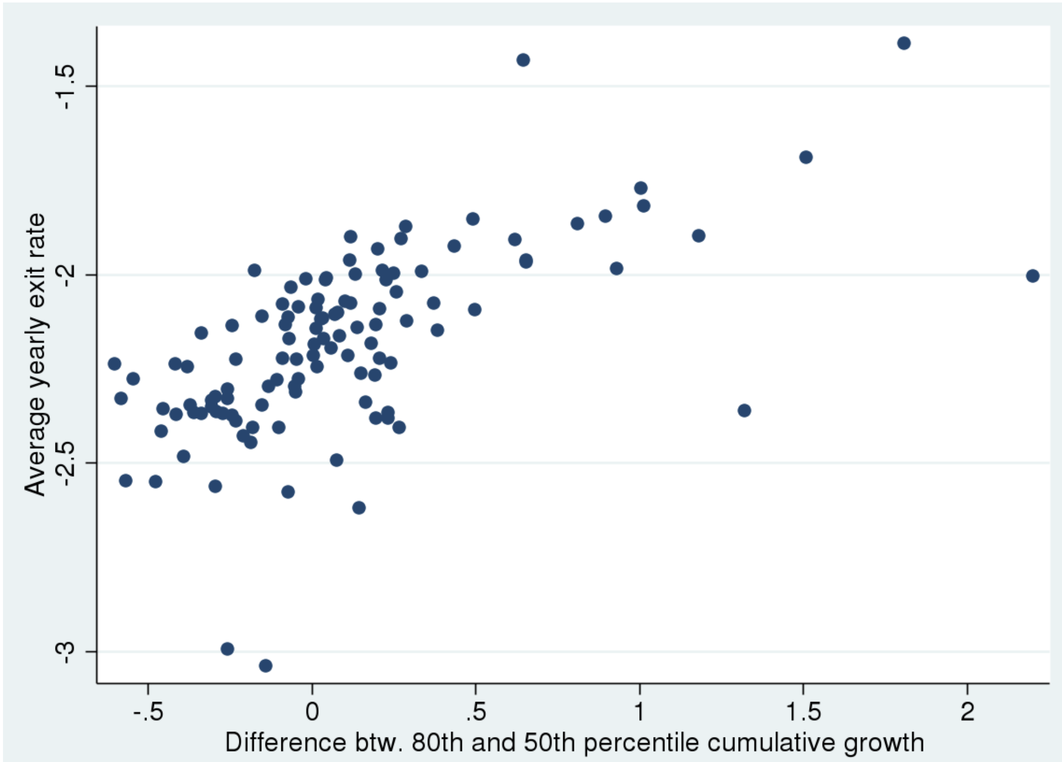

Figure 1: Exit rates and spread in 80th-50th percentile cumulative growth (log units)

implies that poor performing establishments grow even slower which is likely to lead to more exit. A 10 per cent increase in the spread of cumulative growth is linked to a 1.5 per cent increase in exit rates. To interpret this, going from the 10th percentile to 90th percentile industry-year observation in terms of the spread in cumulative growth is associated with a 24.8 percent increase in exit rates. The effect from the level of growth is even larger. A 10 per cent increase in the level of cumulative growth decreases exit by 40 per cent with the difference between the 10th and 90th percentile observation in terms of the level of cumulative growth representing a 39.7 per cent change in exit rates.

Log-log units	**Avg yearly exit rate $<$ 5 yrs**
Spread btw 80th-50th pct of cumulative growth	0.150 (0.018)
65th pct of cumulative growth	-0.408 (0.062)

Table 1: Fixed effects regression

In the bulk of the literature, exit is either exogenous or the result of receiving some shock that pushes an establishment under some exit threshold. The previous result seems consistent with the hypothesis that higher volatility in certain industries leads to a larger spread in growth rates and higher exit. However, this explanation is unlikely for two reasons. Firstly, more volatility in say, productivity shocks, increases the option value of remaining in operation, lowering the exit threshold. Therefore higher exit would be observed with lower spreads in cumulative growth. Secondly, industries with higher exit rates do not have higher volatility as measured by the standard deviation of employment. The correlation between exit rates and the standard deviation of employment is -0.02, indicating a very weak negative relationship. Including the standard deviation of employment in the previous equation results in a coefficient of 0.0001 which is not statistically different from 0. Therefore, it does not appear that differences in volatility underpin the relationship between exit rates and the spread in cumulative growth.

Instead, I interpret the relationship as evidence of some form of rivalry that affects establishment growth. If rivalrous resources are important, an increase in the speed of growth at fast growing establishments must come at the cost of slower growing establishments.[8]

Moreover, slower growing establishments are more likely to exit. To demonstrate this, I use a Probit regression which models the probability of exit as a function of an establishment's cumulative growth, their percentile in terms of cumulative growth relative to others in the cohort and dummies for industry and age. The coefficient on the level of cumulative growth is positive and significant, suggesting that the level of cumulative growth affects exit over and above an establishment's relative position in a cohort. Table 2 reports the average marginal effects and an interpretation based on the variation in cumulative growth. A move from the 10th to 90th percentile surviving establishment in terms of cumulative growth is associated with a 6.7 percentage point decrease in the probability of exit. Taken together, these two facts are capable of explaining why larger spreads in cumulative growth are associated with higher exit rates of entrants.

	Effect on exit rates
Average marginal effect from change in cum. growth	-0.022 (0.001)
10 to 90th pctile-sized change in cum. growth	-0.067 (0.001)

Dummy variables for age, industry and year included.

Table 2: Probit regression on exit

2.2 Wages do not drive selection

Although these results are consistent with the effects of selection in typical models of heterogeneous establishments, it is unclear what the mechanism is that leads faster growing establishments to push out their slower growing counterparts. In standard heterogeneous firms models

[8]In the literal sense, all tangible factors of production are rivalrous when the supply of factors is fixed. However, for a group of establishments operating in a distinct market, resources do not need to be rivalrous within the market as resources can be reallocated from elsewhere.

similar to Hopenhayn (1992), selection is driven by changes in wages or more generally, input prices. As relatively productive establishments are able to accumulate more resources, they increase the marginal products of factors of production bidding up factor prices, squeezing profits and inducing exit of less productive establishments.

To test this mechanism, I ask whether wages across industries are positively associated with exit rates or spreads in growth rates of fast and slow growing establishments. I deflate payroll at each establishment using the Consumer Price Index and calculate the employment weighted average wage across establishments. Weighting by employment is equivalent to finding the average wage across the labor force employed in a given industry. At each date, I take the mean employment weighted average wage over the next 5 years since exit rates for a given cohort are calculated up until age 5. To account for level differences in wages between industries, I regress differences in the log of wages against dummies for each year, and in logs, *(i)* differences in the spread of growth and *(ii)* the level of growth.

	Effect on wages
Spread btw 80th-50th pct of cumulative growth	-0.009 (0.015)
Average yearly exit rate	-0.028 (0.022)

Dummy variables for year included.

Table 3: Regression for average wages (log units)

Theory would suggest a positive relationship between wages and both variables. A larger spread in growth rates between fast and slow growing establishments and higher exit, both reflecting greater intensity of selection should lead to increases in input costs and hence increases in wages. The results in Table 3 instead show a weak negative relationship suggesting that wages do not increase when the spread of growth or the exit rate increases. Of course, because members of a cohort in an industry are not necessary geographically concentrated, one may argue that wages in manufacturing are more or less set at the national level and the lack of correlation between wages and moments that reflect selection is unsurprising. Regardless, the conclusion is the same. Wages are not the channel by which fast growing establishments push out their slower growing counterparts.

One potential explanation that warrants discussion is that the link between the spread of growth and exit simply reflects a process where establishments draw different "trends" in productivity. In this environment, higher exit of a cohort occurs when these trends in productivity span a wider range, with some establishments experiencing larger growth and others declining into the exit threshold faster. While I cannot rule out this theory with the data used in this paper, there is supporting evidence that physical productivity is relatively unimportant in describing exit relative to demand side considerations. Foster et al. (2008) show that the implied 1 year persistence of demand is much higher than of physical productivity, 0.97 to 0.8 and that the level of productivity matters much less than demand in exit. Exiters are only 3 per cent less productive than incumbents but have 64 per cent less "demand" than incumbents. These facts imply that demand side considerations are likely to explain the relationship between the spread of growth rates and exit, rather than a story based on productivity trends.

To provide a theory of selection that does not depend on factor prices, I develop a model in Section 3 where changes in demand-side behavior are an important channel for variation in selection. Instead of increases in factor prices inducing exit, customers can endogenously increase their expectations of the value of from matching and reject matching with some establishments, inducing exit. The idea is that in the data, average entrant quality varies from year to year altering the intensity of selection across time. In years with an above average quality cohort of entrants, the intensity of competition for customers increases inducing exit. Although the model does not feature this type of aggregate uncertainty, the selection mechanism is the same.

2.3 Evolution of cumulative growth

Figures 2 and 3 depicts the evolution of cumulative size over the lifecycle for both the US and Chile, where as discussed above, I use sampling weights to adjust the industry composition to mimic the composition in the US. Bear in mind that the units of measurement are each country's median size by employment. For example, suppose that the median establishment has 25 employees. The top half of Figure 2 suggests that the median establishment in the US adds roughly 0.75×25 workers after 10 years of operation. Viewed on their own, the graphs in Figure 2 show that the cumulative growth distribution fans out over the lifecycle, much like the size distribution does in Cabral and Mata (2003). However, what is interesting is the differences between this fanning out between the US and Chile. After 10 years, the 90th percentile establishment in the US has added 5.25 median establishments worth of workers more than their counterparts in Chile. This positive difference between the fanning out of the distribution in the US and Chile occurs at all percentiles and is monotonic in the percentile. For instance, the 99th and 25th percentile difference between the US and Chile is X and Y respectively.

There are one obvious potential explanation which goes against this interpretation. It may be that growth over the lifecycle may be less important in Chile because high quality establishments have a higher initial size relative to the US and selection forces upon entry are stronger in Chile. Hence observing that the right tail fans out less implies little about allocative efficiency since there is little to no growth to be done in Chile. To show that this is not the case, it is simple to check the size of entrants in both countries. In fact, the median US entrant is *smaller* than the median Chilean entrant.

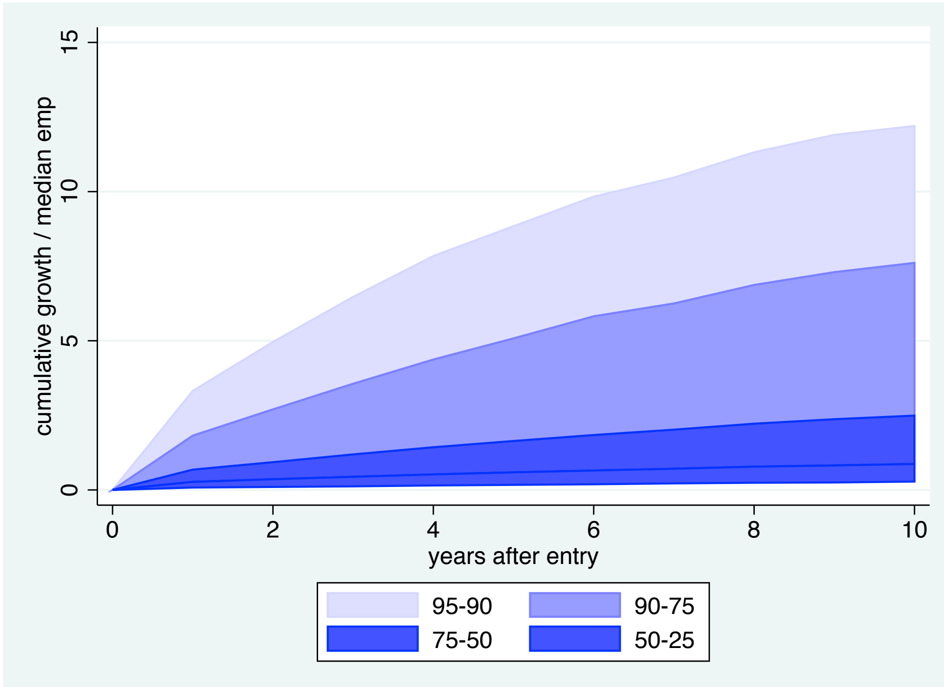

Figure 2: Evolution of cumulative growth in USA

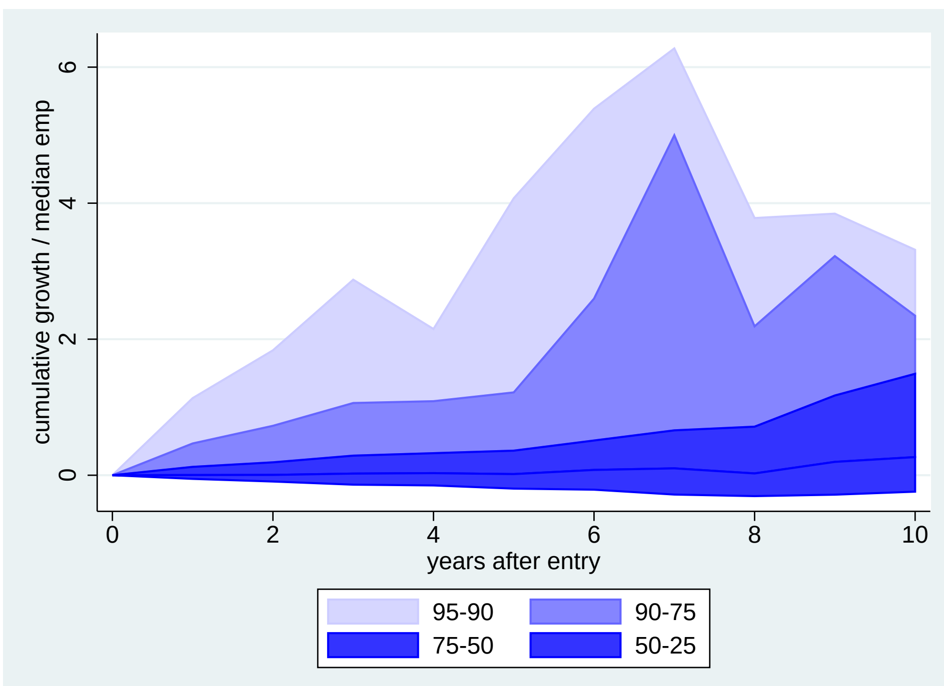

Figure 3: Evolution of cumulative growth in Chile

Initial size	25th	50th	75th	90th	95th
US	7	16	40	92	150
Chile	10	17	35	73	137

Table 4: Entrant size distribution

3 Model

Two stylized facts were presented in the previous section regarding the growth of young manufacturing establishments in the US : (i) increases in the difference between cumulative growth at fast and slow growing establishments is associated with faster exit and (ii) slow growing establishments exit faster. In order to understand how these patterns arise and to quantify their effects on allocative efficiency, I develop a model which is capable of replicating these patterns while matching a rich set of stylized facts. The model embeds two key margins that link an establishment's ability to crowd out other establishments for resources, to the extent of allocative efficiency.

The model is essentially a continuous time version of a standard heterogeneous firms model where firms produce homogeneous goods of varying quality with two additional features. To mimic the productivity advantage that entrants have, the mean of the quality distribution from which entrants draw from is continually growing. This induces an element of vintage capital whereby all establishments are eventually superseded by entrants. Secondly, establishments need to match with customers in long lasting relationships to sell their output. These frictions in product markets capture the idea that demand side frictions may be a source in reducing allocative efficiency.

Establishments produce a good using labor which differs in the amount of utility it delivers to consumers.[9] The simplest interpretation of this is as differential quality across establishments but technically boil down to output sold in bundles for a common price. There exist a mass, L, of individuals who have linear utility in consumption and earn a wage via a frictionless labor market. In order to consume, individuals need to match with establishments. Similarly, establishments need to be matched with a customer to sell a unit of output.

There exists two sources of uncertainty that an entrant faces. Upon entry, entrepreneurs draw a permanent technology for producing goods of a given quality. Search frictions in the product market also induce uncertainty as matches are governed by a Poisson arrival rate. Establishments exit after enough time has passed for the growing technological frontier and the associated entrants to render their technology obsolete. After enough time, the surplus of a continuing or new match becomes negative. New establishments continually drive out the

[9] This is equivalent to an environment with homogeneous goods, where each establishment differs in the amount of goods produced by a single unit of labor with establishments forced to sell goods in bundles.

old by increasing both wages and consumers' outside option in a continual process of creative destruction.

Growth is exogenous and comes from continual growth in entrants quality distribution. Entrants born at time t draw from a Pareto distribution with tail parameter ζ and a lower bound e^{gt}. Given the properties of a Pareto distribution, mean quality of entrants also grows at rate g.

$$G(z;t) = 1 - \left(\frac{e^{gt}}{z}\right)^{\zeta} \tag{1}$$

Later on, the model is solved around the balanced growth path to avoid keeping track of time as a state variable and establishments are identified by their "relative quality at entry", q. A firm born with quality z and at time t_0 has relative quality at entry, or relative to its cohort, equal to

$$q = \frac{z}{e^{gt_0}} \tag{2}$$

Given the existence of search frictions in the product market, the key building block of the model is the surplus from a match between a consumer and establishment. The surplus of a match represents the discounted presented utility from consumption net of wages used in production and the discounted value of being an unmatched consumer upon termination of the match, net of the value of being an unmatched consumer at the beginning of the match. Continual entry by new establishments with on average better production technologies implies that as enough time elapses, the value of continuing the match becomes negative. Depending on the path of prices negotiated, a negative continuation value implies that one of the parties would like to end the match. Establishments would have to accept negative profits (offer discounts) to convince the consumer to remain in the match or the consumer would have to pay more than they receive in utility. I assume that the match is terminated when the continuation value becomes negative, whereupon one party decides to leave the match. Letting U denote the value to an unmatched consumer, the surplus of a match at an a-old establishment born at t_0 is

$$V_j(z, a; t_0) = \max_A \int_a^A e^{-r(t'-a)}(z - \phi w(t_0 + t'))dt' + e^{-r(A-a)}U(t_0 + A) - U(t_0 + a) \tag{3}$$

Note that since utility is linear, prices do not appear in the definition of the surplus as prices are transfers of the numeraire good from individuals to consumers. Bargaining affects the present discounted value of payments made to establishments, but the path of payments is left indeterminate.[10] After taking first order conditions, the termination age of a match only depends on the establishment's quality draw and date of birth, not the age at which the match began. Therefore, all matches at a establishment are terminated at the same date since all matches at

[10] It is easy to show that if the path of prices is monotonic over time, the path of prices must be weakly increasing and strictly increasing if customers have some bargaining power.

a single establishment are characterized by a common level of quality and date of birth. Define this common termination age as the date of exit for the establishment.

$$z = w(t) + rU(A^* + t_0) - U'(A^* + t_0) \tag{4}$$

Since the mean of entrants' quality distribution is growing, I will solve the model around this balanced growth path (BGP). To find the BGP, assume that S and w grow at some arbitrary rate $\hat{g}$. That is,

$$S(t) = Se^{gt} \tag{5}$$

Combining equations (2) and (5) gives the equation that pins down an establishment's exit date as a function of an establishment's relative quality at entry.

$$x = (\phi w + (r-g)S)^{\hat{g}(t_0+A)-gt_0}$$

For a balanced growth path to exist, it must be the case that the date of birth is irrelevant for the exit age of establishments. That is, two establishments born with the same relative quality at birth but in different periods should have the same exit age which implies that $\hat{g} = g$. Note that all costs denominated in terms of the numeraire good have to grow at rate g, otherwise they will converge to zero, relative to the BGP. Using the fact that non-stationary variables on the BGP grow at rate g, it is simple to rewrite the surplus from a job as

$$V_j(q,a) \equiv \frac{V_j(z,a;t_0)}{e^{gt}} = \int_a^{A(q)} e^{-(r-g)(t'-a)} \left(qe^{-gt'} - \phi w\right) dt' + Ue^{-(r-g)(A-a)} - U \tag{6}$$

and the exit age as

$$A(q) = \frac{1}{g}\log\left(\frac{q}{\phi w + (r-g)U}\right) \tag{7}$$

The surplus from a match with an establishment is increasing in q as the flow utility from consumption depends linearly on q and decreasing in a as the level of quality relative to current new entrants declines holding q fixed. An establishment with a higher relative quality at entry exits later, while increases in the wage or value of an unmatched consumer decrease the lifespan of all establishments. The lower bound for relative quality at entry is the value of q that leads establishments to exit instantly, or where $A(\underline{q}) = 0$.

$$\underline{q} = \phi w + (r-g)U \tag{8}$$

Matching between consumers and establishments is governed by an establishment level matching function. Each establishment's matching intensity, $m(s;U,S)$, depends on their marketing efforts, s, aggregate marketing efforts, S and the mass of unmatched individuals searching for establishments.

$$m(s;U,S) = \lambda u \frac{s^\theta}{S} \tag{9}$$

where S is defined as

$$S = \int_{\bar{q}}^{\infty} \int_{0}^{A(q)} s(q,a)^\theta dF(q,a) \tag{10}$$

and $F(q,a)$ is the stationary measure of establishments over the quality-age space. S captures the rivalrous nature of marketing. To increase their own rate of matching, an establishment has to increase their own marketing effort which slows down other establishments rate of matching. The degree to which an establishment can crowd out other establishments is governed by θ. For a given value of S, a higher value of θ increases an establishment's ability to crowd out others in attracting customers. In the limit, as θ approaches zero, matching no longer becomes rivalrous and each establishment receives a homogeneous share of matches. It is likely that θ is less than 1 in reality since factors such as geography limit establishments' ability to reach geographically dispersed customers.

Upon matching, customers enter into a long term agreement with an establishment that specifies the path of prices. Each period prior to termination, they exchange payment for the good and when the match is terminated, they re-enter the search process. Instead of specifying the flow utility each customer receives from some path for prices, it is easier to map the resulting split of the surplus to a Nash bargaining parameter. Upon matching, a customer essentially receives a share of the surplus since the share of the surplus represents the present discounted utility of consumption over the lifespan of the match net of prices and the present discounted utility of re-entering the search process upon termination. Hence, the value to a customer of being unmatched is

$$rU = \lambda(1-\beta) \int \int \frac{s(q,a)^\theta}{S} V_j(q,a) dF(q,a) + gU \tag{11}$$

where r reflects the rate of time preference and β is the bargaining power of establishments. The first term is the share of the surplus from a match at a given establishment, adjusted by a term proportional to the probability of being matched to that establishment. The final term reflects growth of U. Note that if $r < g$, the value of being unmatched increases faster than the rate of time preference implying that it is optimal for customers to remain unmatched, a standard quirk of infinite horizon models.

It is worth noting that although matches are random, customers are satisfied with their match. Ex-ante, they would prefer to be matched with the establishment producing the highest quality good but often accept a match delivering less utility since search takes time and is costly. Establishments exit when customers would rather search again than being matched with them. The randomness in matching and the consequent satisficing is limited by establishments marketing efforts. If establishments can crowd out other establishments easily, higher quality establishments make larger marketing efforts, leading to less satisficing in equilibrium.

Given the Nash bargaining setup, it is simple to set up the establishment's problem. Establishments set their own marketing efforts to maximize the discounted value of profits net of wages required for marketing.

$$\pi(q,a) = \max_{s} \lambda u \frac{s^{\theta}}{S} \beta V_j(q,a) - ws \tag{12}$$

Using the solution to the establishment's problem, and the definition of aggregate marketing efforts, (10), an a-old establishment with relative quality at entry q matches at the rate $m(q,a)$, which is proportional to an establishment's surplus raised to a term increasing in θ, relative to the equivalent in the aggregate. Establishments with a lower relative quality at birth, q, grow at a slower rate as the surplus is increasing in q. Hence establishments that grow at a slower rate, exit at a faster rate as was documented for young establishments in the US. It is clear to see that as θ increases and establishments find it easier to crowd out others, growth rates become more sensitive to an establishment's surplus and the spread in growth rates increases.

$$m(q,a) = \lambda u \frac{V_j(q,a)^{\frac{\theta}{1-\theta}}}{\int_{\underline{q}}^{\infty} \int_0^{A(q)} V_j(q',a')^{\frac{\theta}{1-\theta}} dF(q',a')}$$

Since matching of customers is random and establishments are continually exiting, there exists a constant mass of individuals who are unmatched. Let u represent the mass of unmatched individuals which satisfies

$$L - u = \int_{\underline{q}}^{\infty} \int_0^{A(q)} \int_0^{a} m(q,a') da' dF(q,a) \tag{13}$$

Equation (13) states that the mass of unmatched individuals is the mass of customers minus those that are currently in matches. The number of customers at an a-old establishment with relative quality at entry q is the integral of their matching function over the age domain from birth to age a. Therefore, the mass of matched customers is just the integral of the mass at each establishment over the age-relative quality space taking into account the stationary measure of establishments. It is easy to prove that the equilibrium value of u is between 0 and L.

Labor market clearing equates labor demand from marketing efforts, production and entry with labor supply. Bear in mind that the labor market is frictionless and always clears in equilibrium.

$$L = \int_{\underline{q}}^{\infty} \int_0^{A(q)} s(q,a) dF(q,a) + \int_{\underline{q}}^{\infty} \int_0^{A(q)} \int_0^{a} m(q,a') da' dF(q,a) + c_e e \tag{14}$$

Establishment entry is governed by a free entry condition. To create an establishment, entrepreneurs hire a single worker. Payment is made before receiving the permanent technology draw which leaves open the possibility of entry and instantaneous exit. Entrepreneurs who draw quality below a cutoff level decide to leave instantly where the cutoff satisfies equation (8). The free entry condition states that the expected value of creating a new establishment including the entry cost must be weakly negative. The expected value of an establishment born with relative quality q is

$$V_f(q) = \int_0^{A(q)} e^{-(r-g)a} \pi(q,a) da \tag{15}$$

The expected value takes into account discounting, expected growth and matching at each age due to the randomness of matching and finally, the establishment's share of the surplus upon matching. Nash bargaining is especially useful as I do not need to keep track of the evolution of each match. Instead, every time a match arrives, the establishment effectively receives its share of the surplus which represents the expected present discounted value of that match. The free entry condition can therefore be written as

$$w = \int_{\underline{q}}^{\infty} V_f(q) dG(q) \tag{16}$$

Note that the free entry condition equates expected profits to the cost of entry which implies that some entrants make losses. Because the wage is denominated in the numeraire good which must be purchased via search, there is an underlying assumption that individuals finance entrants in exchange for an equal portfolio of shares in all establishments. On average, individuals make zero profits from this investment which does not affect their decision making since they are risk neutral.

The final piece of the model is the stationary distribution over the quality and age dimensions. Firstly, because exit is deterministic, there are equally as many young firms with a particular relative quality at entry q than there are old firms. There are relatively few old firms as in the data because the probability of drawing a technology for high quality output is low and diminishes faster than lifespans increase with q. Hence the model is capable of matching the data along the age dimension without exogenous exit of establishments. As age is a continuous variable and entry occurs continuously, the pdf of an a-aged firm born with q with a less than the maximum age $A(q)$ is the entry rate times the likelihood of drawing q at birth. If a is greater than $A(q)$, then $f(q,a)$ is 0. Otherwise for $a < A(q)$,

$$f(q,a) = eg(q) \tag{17}$$

4 Estimation

Before proceeding to discuss how the model's parameters are estimated, it is necessary to discuss the dimensions that the model will be unable to fit the data. Since quality draws are permanent, there is obviously no scope for the model to match any data on incumbent innovation. The model generates growth in the aggregate purely through innovation by entrants. As entrants draw quality from a distribution whose mean is continually growing, it may appear as though quality is declining with age, which is completely at odds with the data. However, because exit is endogenous and tied to establishment production quality, only establishments with high enough quality technology survive past a certain age. An establishment needs a relative quality at entry greater than $\underline{q}(a)$ to survive past the age a.

$$\underline{q}(a) = \underline{q}e^{ga}$$

Hence as age increases, exit truncates members of the cohort from the left leaving behind relatively productive establishments. Exit exactly offsets the growth in entrants quality distribution such that the mean level of quality is flat across each age group. To see this, note that the level of quality for an a-old establishment born with relative quality q is

$$z(q, a) = qe^{-ga}$$

and convert the minimum level of relative quality at age a into non de-trended quality

$$z(\underline{q}(a), a) = \underline{q}(a)e^{-ga} = \underline{q}$$

which is the same lower bound as the current entrant distribution. Moreover, depending on the relative growth rates of high and low quality establishments, it may be the case that the *employment-weighted* mean level of quality increases with age, even though there is no incumbent innovation. This provides an alternative interpretation of positive sloping productivity-age profiles that weight establishments or firms by employment. The positive slope may simply reflect greater weighting of establishments with high productivity over time.

In reality, exit is not deterministic with some low quality establishments surviving longer than expected and vice versa for some establishments producing high quality output. The absence of both relatively low quality establishments that persist in spite of their low productivity and the lack of failures among high quality establishments imply that the quality-age correlation in the model is too high. Note that this does not necessarily invalidate the earlier point made before that the mean quality-age profile is flat because it is a statement regarding the composition of exiters and survivors.

Given the limitations of the model, the strategy in this section is to calibrate parameters that are standard and well identified in the data and then estimate the rest of the model to moments in the data that have a clear purpose in identifying parameters. The annual discount rate in the model is set to 3 per cent corresponding to a real interest rate of 3 per cent. Growth in the mean of the quality distribution is set to match the 1.2 percentage points entrants contribute to yearly productivity growth in manufacturing (Foster et al., 2008). By definition, since entrants draw quality randomly upon entry, some establishments detract from aggregate quality growth while others contribute most of the growth. Finally, I normalize the mass of customers and workers, L, to 1 since the mass of workers just scales the economy.[11]

The remaining parameters are estimated to minimize the distance between moments implied by the model and from the data (method of moments). To weight moments equally, I scale each moment such that it reflects the percent deviation from the moment in the data. Ideally, moments would directly identify a single parameter but because the model is highly non linear, most of the following moments identify more than one parameter.

A key parameter of the model is the parameter which reflects the degree to which establishments can crowd out others for customers. This crowding out parameter controls the spread of growth rates with higher values lessening the curvature of an individual establishments matching function with respect to marketing efforts. However, increasing the returns to marketing efforts only benefits a subset of establishments since matching with customers is rivalrous. Although all establishments increase marketing efforts as crowding out becomes easier, marketing efforts from high quality establishments increase by relatively more. These effects of the crowding out parameter map directly to two moments: the share of employment in manufacturing devoted to selling and the evolution of the size distribution over the lifecycle.

Using data from the Bureau of Labor Statistics Occupational Employment Statistics on manufacturing employment in May 2011, I categorize occupations into production, selling and distribution or neither. I interpret marketing efforts as expenses that are separate from production and relate directly to creating and sustaining demand. These include marketing staff, sales persons and delivery drivers. The detailed list of these categories is available in the Appendix. Excluding occupations categorized as neither production nor selling and distribution, occupations categorized as part of selling and distribution account for 17 per cent of payroll.

To capture the spread in growth across fast and slow growing establishments, I target the cumulative growth in employment of survivors after 10 years adjusted for median employment. Although it is easy to calculate cumulative growth or simply size as all establishments start at the same age, the median is slightly more difficult. The median establishment by employment is not simply the median surviving establishment of a cohort because establishments born with

[11] It is easy to show that the solution of the model is not affected by L. Although moments relating to levels such as output changes, relative differences such as the percent decrease in output from changes in parameters remain the same.

a relatively high quality technology last longer than those born with relatively low quality technology. For example, although many entrants are born with relative quality at or below the exit threshold, none of these establishments count in the calculation of the median since they exit instantly. To find the median, I use the "median of medians" algorithm. Firstly, I find the median relative quality by solving the following equation for $q_{0.5}$

$$0.5\int_{\underline{q}}^{\infty} A(q)\zeta\frac{1}{q^{\zeta+1}} = \int_{\underline{q}}^{q_{0.5}} A(q)\zeta\frac{1}{q^{\zeta+1}}$$

and then find median employment for the median relative quality establishment. I calculate the spread of growth as the difference between the median and 90th percentile establishment in terms of median employment after 10 years. The spread in US data from Figure 2 is 6.82 median establishment's worth of workers.

The evolution of the cumulative growth distribution after 10 years is also informative about the speed of growth. After 10 years, the median surviving establishment is 0.82 times the size of the overall median establishment. I use this moment to help identify the level of the matching function, λ and the bargaining parameter, β. Although matching for establishments is rivalrous, the aggregate level of matching is λu which implies that increases in λ should increase the speed of growth. Variation in β affects the level of growth over the lifecycle through the mass of unmatched workers. Establishments invest more heavily in marketing efforts when their bargaining power is increased, reducing the mass of unmatched workers and increasing the intensity of aggregate matching.

Because the quality distribution entrants draw their technology from is Pareto, a single tail parameter, ζ, characterizes the quality distribution. A higher tail parameter spreads out the quality distribution increasing both the mean and variance of quality among entrants. The first clear effect on moments in the model is in the skewness in growth and size. Larger variance in relative qualities increases the variance in the surplus of matches and hence growth rates. As a simple measure of skewness, I calculate the difference between mean and median employment among manufacturing establishments. Over the period 1976 to 2000, the mean establishment is 3.81 times the size of the median establishment, in terms of employment.

A less obvious effect of changes in the tail parameter is on exit rates. As the tail parameter increases, entrants are on average more productive and displace more incumbents. One can show that the mass of establishments is equal to

$$M = e\underline{q}^{-\zeta}\frac{1}{g\zeta}$$

Given that a mass e continually enters and $\bar{q}^{-\zeta}$ of a cohort does not instantly exit, $g\zeta$ reflects the exit rate of the cohort of establishments excluded those that do not instantly exit. Alternatively,

$\frac{1}{g\zeta}$ is the average age of establishments that survive past birth. The growth rate of the entrant distribution affects exit as higher growth rates of entrants' productivity distribution increases the mass of establishments with better productivity than incumbents and hence displacement. In the model, there is a bunch of exit at birth and then a constant hazard of exit thereafter whereas the data show a smoothly declining hazard of exit. The smoothness in the decline in exit rates probably reflects some element of learning which would delay part of the instantaneous exit. Because the econometrician does not observe instantaneous exit, I match the the constant hazard of exit in the model against the average exit rate in the data, 0.11.

Moment	**Data**	**Model**	**Source**
Mean / median employment	3.81	5.68	US Census synthetic LBD (manufacturing)
Median cumulative growth after 10 yrs / median employment	0.89	0.82	US Census synthetic LBD (manufacturing)
Spread of 90-50th percentile cumulative growth after 10 yrs / median employment	6.74	6.03	US Census synthetic LBD (manufacturing)
Average exit rate	0.11	0.17	US Census Business Dynamics Statistics
Selling and distribution workers' share of payroll in manufacturing	0.17	0.22	Bureau of Labor Statistics Occupational Employment Statistics - May 2011

Table 5: Moments from the data and the model

A summary of these moments from both the data and the model at the estimated parameters are shown in Table 5. Overall, the model does a reasonable job of matching moments from the data. As stated earlier, the measure of skewness captured by the mean/median employment difference is slightly high at 5.68 compared to the value of 3.81 in the data because of the overly tight connection between exit and quality. The median surviving establishment is 0.82 times the size of the median establishment, close to the value of 0.89 in the data suggesting that the model captures the median level of growth well. While the spread between the 90th and 50th percentile establishment in terms of cumulative growth is 6.74 in the data after 10 years, it is only 6.03 in the model. Since the model more or less matches the level of median growth, the divergence between model and data comes from the right tail suggesting that fast growing establishments do not grow fast enough. Finally, the model comes close to matching the data in terms of selling and distribution workers' share of payroll. A slightly higher share of payroll, 22 per cent, is accounted for by selling and distribution workers than in the data, 17 per cent. The calibrated and estimated parameters are shown in Table 6.

Parameter	Calibrated Value
r - real interest rate	0.03
L - mass of workers	1
g - growth of entrant Productivity distribution mean	0.012
	Estimated Value
ζ - tail parameter for Pareto distribution	9.551
β - establishment share of surplus	0.809
ϕ - workers needed to produce a unit of output	0.739
λ - scale of matching process	0.523
α - curvature in matching process	0.577

Table 6: Estimated and calibrated parameter values

5 Results

In this section, I ask two questions of the model. What are the relative roles of input costs and changes in demand-side behavior in determining the intensity of selection? What can we infer regarding allocative efficiency from the differences in the evolution of cumulative growth in the US and Chile? To answer these questions, I assume that changes in the spread of growth between fast and slow growing establishments are driven by differences in the degree to which establishments can crowd out other establishments. I discipline the magnitude of the change in the parameter that controls the degree of crowding out, θ, by matching the spread of growth between the 90th-50th percentile establishments in Chile. The 90th-50th percentile spread after 10 years in Chile is 3.05 median establishments which I match by reducing θ from 0.577 to 0.556.

Reducing θ decreases the marginal returns to marketing efforts and the ability for establishments to crowd out others for customers. High quality establishments, who accumulate the bulk of customers by disproportionately using marketing efforts in equilibrium, suffer the most when the ease of crowding out lessens. Customers and production flow from establishments producing high quality goods to lower quality producers. The effect of this reallocation on selection is two fold. As in typical models with selection, reallocation to lower quality establishments lowers labor demand as both marketing efforts in the aggregate and production fall, decreasing wages. This is the standard channel whereby input costs drive selection. The second effect is more subtle, coming from changes in customers matching behavior. As the matching rate decreases at establishments producing high quality goods, who promise relatively high utility from matches, and increase at lower quality establishments who promise lower utility, customers expected value from matching falls. Hence when considering whether to accept a match with a low quality producer against returning to search, customers are more likely to accept the match which effectively lowers the exit threshold for establishments. Some establishments who would otherwise be ignored by customers and exit now attract a small number of customers and remain in operation.

To decompose these effects, note that the exit threshold which governs establishment lifespans is given by the following equation.

$$\underline{q} = \phi w + (r - g)U \tag{18}$$

Changes in the exit threshold are the primary mechanism by which selection operates. Hence I decompose the effect on selection from changes in wages and changes in customer behavior baed on this equation. Using this decomposition, 58 per cent of the lessening in selection comes from changes in customer behavior. In other words, customer behavior can be an equally, if not more important factor in selection than increases in input costs in the model.

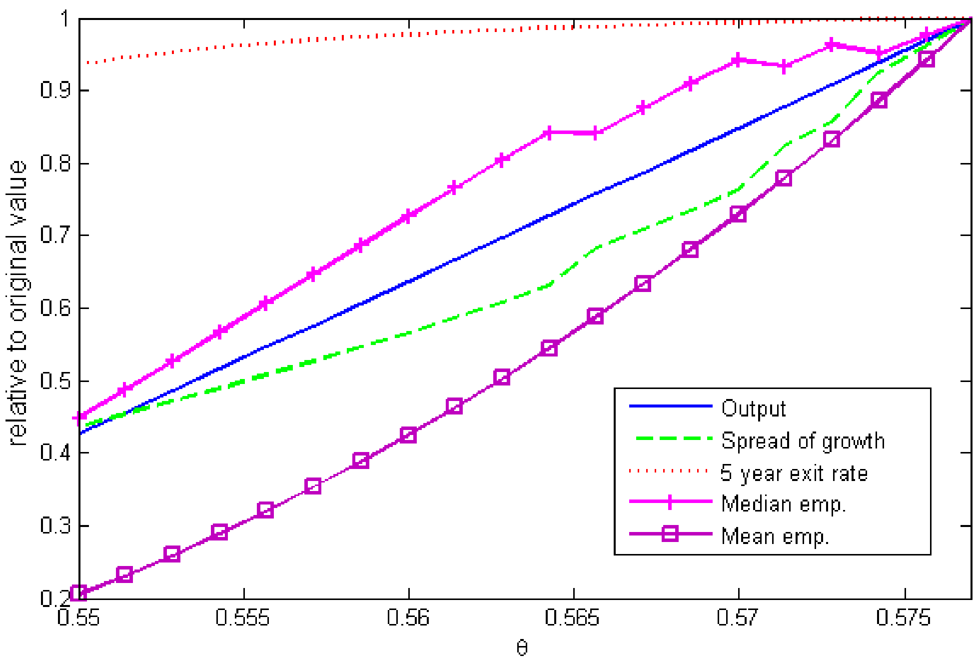

Figure 4: Effect of θ on moments relative to values at estimated parameters

Figure 4 depicts the moments of the model calculated at various values of θ, starting at 0.55 and ending at the estimated value of 0.577. Each point on the line represents the value of a moment from the BGP, or stationary equilibrium, of the model at a given value for θ. It is clear from the figure that the reduction in θ generates a large response. As mentioned earlier, as the spread of growth rates fall, welfare falls as production and customers are reallocated from high to low quality establishments. Exit falls as lower quality establishments which would otherwise be forced to exit due to a lack of demand remain in operation by attracting a relatively small number of customers. The elasticity between the spread in growth rates and exit is roughly 0.11, close to the value estimated in data. This reallocation additionally manifests as a reduction the skewness in employment across establishments, which can be inferred from the shrinking in the gap between mean and median employment. Using the spread in growth rates in Chile to discipline the reduction in θ, the model suggests that welfare falls by roughly 44 per cent due to such a change.

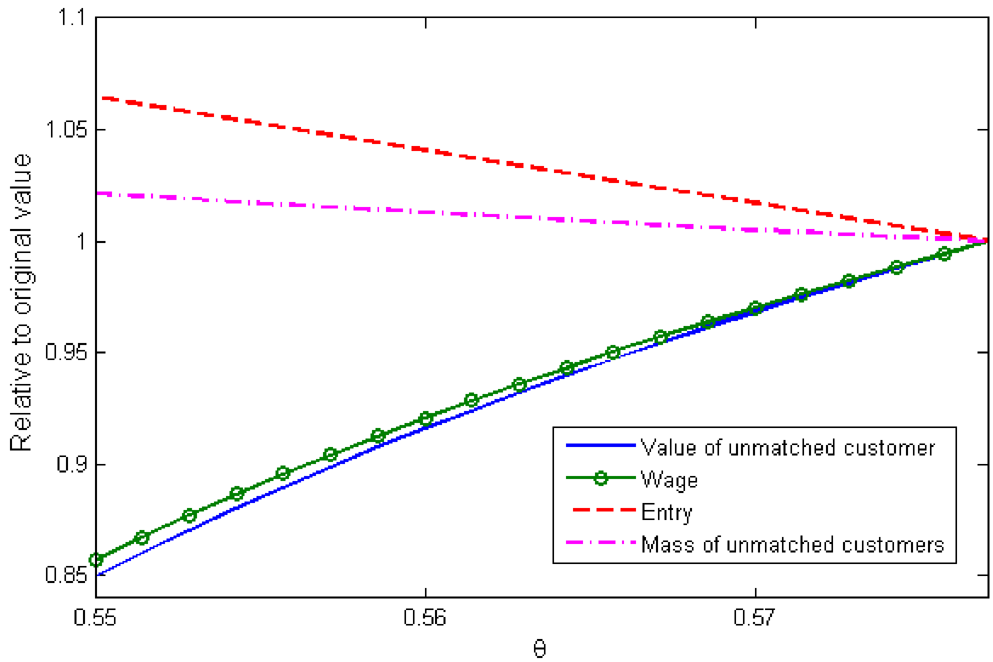

Figure 5: Effect of θ on model relative to values at estimated parameters

The bulk of the negative effects come from the reallocation of production. Figure 5 shows that as production and customers are reallocated, both wages and the value of an unmatched customer fall by roughly 10 per cent. Wages fall in response to the reduction in labor demand by establishments producing high quality goods. As labor supply is fixed, wages need to decrease to induce an increase in hiring by other establishments and to mitigate the reduction in hiring by high quality establishments. To see this note that in equilibrium, an a-old establishment born with relative quality q has marketing efforts equal to

$$s(q,a) = \frac{\lambda u \beta \theta}{w} \frac{V_j(q,a)^{\frac{1}{1-\theta}}}{V} \tag{19}$$

A reduction in θ has both level and relative effects. Holding wages fixed, responses in u, θ and V generate level effects that affect all establishments' labor demand equally. However, the idiosyncratic part of labor demand for an establishment, it's surplus from matching, is interacted with θ generating a relative effect. Establishments with a very large surplus from matching experience a much larger reduction in labor demand relative to establishments with low surpluses from matching, holding wages fixed. The consequent decrease in wages required to clear the labor market generates a counteracting level effect. The overall effect on labor demand will be negative for an establishment with large enough surpluses from matching, as the relative effect on the idiosyncratic part of labor demand outweighs the level effect. Since the opposite occurs for establishments that generate low enough surpluses from matching, labor and customers are reallocated from high to low quality establishments.

This reallocation of labor is evident in the close to 50 per cent reduction in the spread of growth rates in Figure 4. As it becomes less likely that any given unmatched customer will be matched with an establishment offering relatively high promised utility, the value of being an unmatched customer falls. Underlying this mechanism is the assumption that customers know the distribution of establishments productivities/promised utilities from matching, but are unable to identify any given establishment's promised utility prior to matching. For example, imagine a consumer choosing a hybrid automobile who knows there are good and bad automobiles, yet is unaware whether a Toyota Prius is good or bad. Upon walking into a Toyota dealership, the customer takes a test drive and discovers the stream of promised utility the Toyota Prius offers. A decrease in U in this environment is simply a reduction in the value of returning to search. If the expected promised utility of returning to search falls, the consumer becomes less likely to walk away from a match. In other words, some establishments who would otherwise have had customers walking away from matches, are now able to accumulate customers. In the model, a decrease in the crowding out parameter leads U to fall by roughly 10 per cent, reflecting greater satisficing.[12]

Offsetting the negative effects on allocative efficiency are the responses of establishment entry and the mass of unmatched customers. By construction, as the expected value of creating an establishment is finite, the Pareto distribution for qualities declines faster than the discounted value of operating an establishment with at birth relative quality, q, increases. Therefore, any reallocation from high to low quality establishments must increase the ex-ante value of starting a new establishment, increasing the mass of entry in equlibrium.

To see why the mass of unmatched customers falls, note that u satisfies the following equation.

$$u = L \frac{1}{1 + \frac{\lambda}{V} \int_{\underline{q}}^{\infty} \int_{0}^{A(q)} \int_{0}^{a} V_j(q, a')^{\frac{\theta}{1-\theta}} da' dF(q, a)} \tag{20}$$

Note that entry does not affect u directly since both V and the pdf $f(q, a)$ are linear in e. It is simplest to decompose the effect on θ into two components. The first is the change in $\frac{V_j(q,a)^{\frac{\theta}{1-\theta}}}{V}$

[12]Technically, customers are always satisficing as there is no upper bound on the distribution of relative productivities upon entry.

which is positively related to θ. The next effect is the indirect effect on $A(q)$ from changes in the wage and the value of an unmatched customer. As θ increases, the age of any given establishment, $A(q)$, shortens as the exit threshold $\underline{q}$ increases. Given that these effects go in opposite directions, and u is positively related to θ, it must be the case that the effect of exit and the corollary changes in lifespan dominate the effect on the surplus on matching. In simpler terms, when production and customers are reallocated to lower quality establishments, the dominant effect is the lowering of the exit threshold and the resultant increase in lifespans which implies that any given match lasts longer. As outflows from the pool of unmatched customers occurs at constant intensity λ, and the rate reentry to the pool of unmatched customers falls, the mass of unmatched customers falls.

6 Conclusion

Selection plays a large role in models of heterogeneous establishments, but little is known about how selection operates in reality. In models of heterogeneous establishments, the removal of distortions or frictions that reallocate production to relatively productive establishments increases selection, inducing exit of less productive establishments. The increase in exit is typically generated by the bidding up of input costs by productive establishments. In this paper, using establishment level data in manufacturing, I identified a relationship between the spread of growth between fast and slow growing young establishments and exit rates of young establishments which I interpret as evidence of selection. However, wages do not appear to increase in periods of increased selection which is at odds with how selection operates in typical models.

I developed a model capable of matching a rich set of facts on establishment dynamics and show that changes in demand side behavior can drive selection in addition to changes in input costs. The estimated/calibrated model suggests that as much as 60 per cent of the movement in selection can be attributed to changes in demand side behavior. In particular, with search frictions in the goods market, customers willingness to refuse a match and return to search is a margin that affects selection. Establishments are forced to exit when customers reject matches with them. This result is consistent with the recent literature that emphasizes the importance of demand in understanding establishment/firm dynamics (Fishman and Rob, 2003; Foster et al., 2008, 2012).

A common feature of the early misallocation literature is that aggregate productivity essentially boils down into two components: the level of productivity, and the correlation between size and productivity which captures allocative efficiency (Bartelsman et al., 2009). Here, I take seriously the notion that establishments start small and analyse how growth patterns can be informative regarding allocative efficiency. The main feature of the model is that large dispersion in growth rates between fast and slow growing establishments are indicative of resources are being allocated relatively efficiently. To obtain a large positive correlation between productivity and size, an economy needs relatively high dispersion in growth rates of young establishments. Note that this statement is agnostic regarding the mean or median growth rate of establishments, which may be informative about productivity growth, but irrelevant in terms of allocative efficiency. In the model, a small increase in the curvature parameter of the establishment-level matching function, which governs the rate of establishment growth, leads to reallocation of both production and customers to high quality establishments and a large improvement in allocative efficiency. The model suggests a reduction in the curvature parameter that matches the slower degree of fanning out of the cumulative growth distribution in Chile relative to the US would lead to a fall of 44 per cent in welfare.

7 Appendix

An equilibrium consists of establishments and individuals taking the following as given

- surplus from a match - $V_j(q,a)$: (6)
- matching technology for each establishment - $m(s,u;S)$: equation (9)
- aggregate marketing efforts - S: equation (10)
- value of owning an establishment of quality q - $V_f(q)$: equation (15)
- profits at establishment with quality q and age a - $\pi(q,a)$: equation (12)

while behaving optimally

- establishments and customers terminating matches when privately optimal - $A(q)$: equation (7)
- establishments exiting when they cannot match with customers - $\underline{q}$: equation (8)
- establishments' marketing efforts maximize profits - $s(q,a)$
- individuals reject matches and return to search optimally with full information - U: equation (11)

with "markets" clearing

- labor markets clear: (14)
- customer markets clear given search technology and marketing efforts: (13)
- free entry condition weakly holds: (16)

7.1 Definition of equilibrium

7.2 Solution algorithm

The model can be simplified into 4 equations, representing the equation that defines the mass of unmatched customers, the labor market clearing condition, the definition of the value of unmatched customers and the free entry condition.

$$u = L\frac{1}{1+\frac{\lambda}{V}\int\int\int V_j(x,a')^{\frac{\theta}{1-\theta}}da'dF(x,a)} \tag{21}$$

$$w = \frac{\lambda\theta\beta u}{(u-c_e e)V}\int\int V_j(x,a)^{\frac{1}{1-\theta}}dF(x,a) \tag{22}$$

$$(r-g)U = \lambda(1-\beta)\int\int\frac{s(x,a)^\theta}{S}V_j(x,a)dF(x,a) \tag{23}$$

$$w = \int_{\underline{x}}^{A(x)}\int_0^a e^{-(r-g)a}\lambda u\beta\frac{V_j(x,a)^{\frac{1}{1-\theta}}}{V}(1-\theta)\,dadG(x) \tag{24}$$

Note that there are 4 equations and 4 unknowns, U, u, e, w after substituting for the definitions of $V_j(.), A(x), S, s(x,a), \underline{x}$ and V. The algorithm is a simple fixed point algorithm

1. Guess U_0, w_0, e_0.
2. Update u_1, w_1, U_1 and e_1 via the above equations
3. Calculate difference in values and start at first step if difference large enough.

7.3 Manufacturing occupations

Production	**Selling and Distribution**
Production occupations	Sales and Related Occupations
	Arts, Design, Entertainment, Sports, and Media Occupations
	Advertising and Promotions Managers
	Marketing Managers
	Sales Managers
	Heavy and Tractor-Trailer Truck Drivers
	Light Truck or Delivery Services Drivers

Source: BLS Occupational Employment Statistics - May 2011

Table 7: Categories of manufacturing employment

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